Climate Risk Management Strategies in Agriculture – The Case of Flood Risk

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Abstract

We develop a theoretical and empirical framework to analyze farmers' responses to extreme climate events. Our analysis extends earlier research by investigating measures taken at the whole farm level including on- and off-farm decisions as well as their interactions. To this end, a theoretical model capturing on- and off-farm decisions of farm households under risk is developed and used to derive hypothesis for empirical applications. Our empirical analysis focuses on the case of floods in UK agriculture and makes use of farm-level panel data for the period 1990-2011. Dynamic panel models are estimated for off-farm income and the diversity of on-farm portfolios following the Arellano and Bover/Blundell and Bond GMM system approach. In these models, the effect of floods as well as interactions between farm and farmer's characteristics and risk-reducing strategies are estimated by controlling for biophysical, economic and policy conditions. We find that both on- and off-farm risk management strategies are followed by farmers in response to flood occurrences. These strategies are, however, not independent from each other. Higher off-farm employment is found to be associated with less diverse, i.e. more risky, on-farm portfolios. Thus, on-farm adaptation responses to flood risks are ambiguous. Our analysis thus also reveals general implications for adaptation behavior. Increasing risks and the more frequent occurrence of extreme climate events, e.g. in the context of climate change, may not necessarily lead to an increased use of on-farm risk management strategies. In contrast, if farmers can allocate more resources off the farm, adaptation behavior may even result in more risky production systems.

Keywords: extreme events, flood, risk management, GMM estimator, UK

JEL codes: Q12, D81, C23

1. Background and Motivation

Effects of climate variability and climatic extreme events on agricultural production and the agricultural sector at large receive particular attention (e.g. Goodwin 2008; Gornall et al. 2010; Tack et al. 2012). Next to its economic and policy relevance, this topic is also central for the analysis of potential impacts by climate change on agriculture (e.g. Lobell et al. 2011; Ortiz-Bobea and Just 2013; Schlenker et al. 2005). It has been highlighted that the consideration of adaptation responses is crucial in order to realistically assess potential impacts of (changes in) climate risks (Di Falco et al. 2011; Risbey et al. 1999; Robertson et al. 2012), and thus is necessary for the development of policies supporting climate risk management. However, the current understanding of if and how adaptation is taking place is still very limited (Berrang-Ford et al. 2011).

In order to investigate potential adaptation responses of farmers with respect to climate related extreme events such as droughts or floods, existing research often relies on surveys and modeling approaches (see e.g. IPCC 2007; Smit and Skinner 2002, for overviews). Furthermore, and important for this study, there has been a focus on the identification of revealed adaptation responses taken by farmers to extreme events (e.g. Alem et al. 2010; Dang et al. 2009; Smit et al. 1997). This approach has been motivated by the fact that most adaptation activities have been reactive in response to a shock (Orlove 2005; Zilberman et al. 2012). It has been shown that long-term changes in objective probability distributions, e.g. caused by climate change, are usually not the primary motivator for adaptation action

(Berrang-Ford et al. 2011). In contrast, extreme events are often the main trigger for adaptation responses. This observation is explained by the fact that extreme events act as an 'availability heuristic' (Tversky and Kahneman 1974) altering the perception of risks (Slovic 1987)[1]. This formation of risk perception is in line with the finding of Menapace et al. (2013) that farmers that have experienced substantial losses usually have a higher perception of (climate) risk probabilities, which is finally shaping their adaptation responses (IPCC 2007; Smit and Skinner 2002).

Empirical evidence underlines the relevance of climate extreme events for inducing adaptation responses of farmers. For instance, Ding et al. (2009) find that the occurrence of droughts increases the adoption of conservation tillage practices in subsequent years. Along these lines, Smit et al. (1997) showed that the selection of corn varieties was influenced by weather conditions in previous years. Moreover, an increase in farmers' participation in hail insurance after a major hail event was observed by Finger and Lehmann (2012). Alem et al. (2010) find that rainfall levels in previous years but also the variability of rainfall influences farmers' fertilizer use decisions. Smit et al. (1996) consider a wider set of adaptation responses by farmers and could show that the frequency of dry years was the key climatic stimulus to adjustments of farm-plans, even though economic forces (e.g. changes in prices) were the main driver of changes of farm plans. Also counter-intuitive actions taken by farmers in response to higher (climate) risks have been observed. For instance, Bradshaw et al. (2004) find that, despite increasing climate risks, Canadian farmers increased the riskiness of their on-farm portfolio by using less diverse crop portfolios over time.

Even though a wide range of evidence exists for farmers' adaptation responses to climate stimuli in form of climate related extreme events (see e.g. by Anwar et al. 2012; Bryan et al. 2009; Mechler et al. 2010; Smithers and Smit 1997, for overviews), the current literature in this field reveals significant shortcomings. First, there is a lack of empirical studies based on household level data, which is even more apparent regarding the use of panel data (Alem et al. 2010; Bryan et al. 2009). Second, the relevance of economic drivers for adjustments in farm management decisions has been often neglected (e.g. Alem et al. 2010). Third, these studies focus on specific adaptation responses at the field scale (e.g. changes in tillage intensities or input use), and do not evaluate adjustments at the whole-farm level by focusing on the on-farm use of resources. However, we expect that considering wider sets of on- and off-farm adaptation responses is of crucial importance because farmers tend to adjust their entire farm portfolio in response to potential extreme events (e.g. Pivot and Martin 2002). Thus, adaptation in response to shocks includes the entire set of activities available to the farmer (Zilberman et al. 2012). Such adaptation responses may comprise decisions on capital use as well as land market and farm exit decisions. Furthermore, and important for our study, this also comprises adjustments in off-farm labor allocation decisions, which are an important determinant of farmers' risk management decisions (e.g. Mishra and Goodwin 1997, 1998).

To fill gaps in this literature we provide a conceptual and empirical framework to investigate adaptation measures in response to climate related extreme events at the household level including on- and off-farm decisions made by farmers. To this end, a theoretical model of on- and off-farm decisions under risk at the household level is developed and is used to derive hypotheses for empirical analyses. Moreover, an econometric framework is developed that allows us to investigate farmers risk adaptation decisions using dynamic panel models and is used in an empirical application. More specifically, we focus our analysis on adaptation strategies followed by farmers in the UK to cope with flood events. Floods are of exceptional

[1] Along these lines, Shafran (2011) provides evidence that decision makers weight recent outcomes more heavily than older outcomes.

importance for the UK and its agricultural production as it has been among those EU countries mostly affected by flooding (e.g. Hall et al. 2005; Wheater 2006). Our analysis is based on a comprehensive farm-level panel data set covering the period 1990-2011 comprising about 15,000 observations. The use of a panel dataset enables us to identify lagged adaptation responses and to account for a wide array of drivers that potentially influence farmers' behavior. To this end, financial and business data is enriched by site-specific information on environmental conditions and dynamics. In particular, we account for the timing and severity of flood events and their impact on farmers' decision making.

2. Theoretical Framework

The farm-level household income π_H consists of income generated on- and off- the farm denoted by π_F and π_O, respectively: $\pi_H = \pi_F + \pi_O$. The expected level of income generated by on-farm activities is $\pi_F = l'\pi_f$, where l is a vector summarizing the on-farm labor allocation to i=1,….,n on-farm activities and π_f represents the vector of expected profits per unit labor input of these activities. The income generated off the farm is $\pi_O = ow$, where o is the labor allocated to the off-farm activity and w is the remuneration of this activity (e.g. the wage level). The total labor resource available to the farm household L is allocated either on or off the farm[2], so that $L = \sum_{i=1}^{n} l_i + o$. Off-farm activities are considered to be risk-free[3]. In contrast, income generated from on-farm activities is assumed to be random variable[4], with variance $\sigma_{\pi_F}^2 = l'\sigma_{\pi_f}^2 l$. The household income π_H is used for consumption and under the assumptions of non-satiation, the utility function of the household can be written as $U(\pi_H)$. We assume this utility function to represent risk aversion so that $\partial U/\partial\pi > 0$ and $\partial^2 U/\partial\pi^2 < 0$. Maximizing the expected utility $EU(\pi_H)$ is equivalent to maximizing the certainty equivalent (e.g. Chavas, 2004):

$$CE = E(\pi_H) - 0.5rE[\pi_H - E(\pi_H)]^2 \quad (1)$$

E is the expectation operator based on *subjective* probability distributions of random variables (Chavas 2004) and r represents the Arrow-Pratt absolute risk aversion coefficient $r = -(\partial^2 U/\partial\pi_H^2)/(\partial U/\partial\pi_H)$, with $r > 0$ for a risk averse decision maker. The second part of the right hand side of equation 1 (i.e. $0.5rE[\pi_H - E(\pi_H)]^2$) represents the risk premium R, i.e. the (implicit) costs of risk for the decision maker, which for a risk averse decision maker is $R > 0$.

2.1. Farm household model

Next, we introduce some specifications to the general setup presented above, drawing on earlier work by Robinson and Barry (1987) and McNamara and Weiss (2005). The resulting simple farm household model allows us to derive hypotheses on farmers' behavior with respect to off-farm allocation of labor and on-farm diversification that will be tested empirically. Profits of farm activity i are a function of labor devoted to this activity l_i, i.e. $\pi_i = \pi_i(l_i)$. For illustration purposes, the underlying production functions as well as output prices are assumed to be identical across activities. This allows us to express the on-farm

[2] We follow Mishra and Goodwin (1997) and assume that leisure decisions are exogenously determined and thus do not affect the total labor available at the farm.
[3] See e.g. Kyle (1993) for an analysis that comprises risky off-farm activities.
[4] We focus our analysis on optimal diversification and labor allocation under risk. Analyses of land allocation decisions under production risk are surveyed and provided, for instance, by Blank (2001), Collender and Zilberman (1985) and Popp and Rudstrom (2000).

diversification by the number of farm activities n chosen. Furthermore, we focus on a linear production process so that we can express profits for a farm activity i as $\pi_i = \pi_f l_i$. We consider costs arising from diversification, for instance, due to costs of establishing new activities (such as for learning and supervision) and foregone gains of specialization caused by more diverse production by a term $nc(n)$. These costs of diversification increase in the level of n at an increasing rate so that $\partial c(n)/\partial n > 0$ and $\partial^2 c(n)/\partial n^2 > 0$. Following McNamara and Weiss (2005), we furthermore assume that variances and covariances are equal across activities, i.e. $\sigma_{ii} = \sigma_k^2, \forall i = 1, \dots, n$ and $\sigma_{ij} = \rho\sigma_k^2, \forall i \neq j = 1, \dots, n$ with $-1 \leq \rho \leq 1$. The resulting expected income at the household level containing on- and off-farm profits is defined as as follows:

2 $$\pi_H = \sum_{i=1}^{n} l_i \pi_f + ow - nc(n) = \pi_f(L - o) + ow - nc(n).$$

Due to the risk free nature of off-farm income, the variance of household income can be expressed as $\sigma_{\pi_H}^2 = n^{-1}(L-o)^2[1 + (n-1)\rho]\sigma_k^2$ (Robison and Barry, 1987). Our model thus reflects the valid assumption that household income variance is decreasing in the level of on-farm diversification: $\partial\sigma_{\pi_H}^2/\partial n = -n^{-2}(L-o)^2\sigma_k^2(1-\rho) < 0$ (e.g. Di Falco et al., 2010). Throughout our analysis, we assume that $\rho < 1$, so that on-farm risk reduction is actually feasible. Reflecting farm-level evidence, this risk reducing effect diminishes with increasing levels of diversification, i.e. $\partial^2\sigma_{\pi_H}^2/\partial n^2 = 2n^{-3}(L-o)^2\sigma_k^2(1-\rho) > 0$ (Popp and Rudstrom 2000).

The resulting household-level certainty maximization problem is:

3 $$CE = \pi_f(L - o) + ow - nc(n) - n^{-1}0.5r(L - o)^2[1 + (n-1)\rho]\sigma_k^2$$

2.2. Off-farm labor allocation

The certainty equivalent maximizing level of off-farm labor allocation requires the following first order condition to hold:

4 $$\partial CE/\partial o = -\pi_f + w + n^{-1}r(L - o)[1 + (n-1)\rho]\sigma_k^2 = 0$$

Based on this first order condition and using the implicit function theorem, optimal labor allocation changes in response to changes in other model parameters can be derived in comparative static analyses. First, we can show that the optimal off-farm labor allocation, o^*, increases in the off-farm wage level:

5 $$\partial o^*/\partial w = -(\partial^2 CE/\partial o\partial w)/(\partial^2 CE/\partial o^2) = -1/-n^{-1}r[1 + (n-1)\rho]\sigma_k^2 > 0,$$

if $\rho > -1/(n-1)$, i.e. the on-farm risk reduction potential is not too large (McNamara and Weiss 2005), preventing that risk reduction measures are taken solely on and not off the farm. Second, the allocation of labor to risk free off-farm employment increases with increasing risk aversion:

6 $$\partial o^*/\partial r = -(\partial^2 CE/\partial o\partial r)/(\partial^2 CE/\partial o^2) = -n^{-1}(L - o)[1 + (n-1)\rho]\sigma_k^2/ -n^{-1}r[1 + (n-1)\rho]\sigma_k^2 > 0$$

Note that if two farmers have the identical production and off-farm opportunities but differ with respect to their risk aversion, the separation theorem states that they will use the same on-farm portfolio but differ with respect to the on- and off-farm allocation of labor resources. This is due to the fact that it is always possible to illustrate the choice set available to the farmer as a combination of a portfolio containing risky on-farm assets and another portfolio that holds only the riskless off-farm portfolio component (see e.g. Simmons 2002).

Third, off-farm labor allocation decreases with increasing profitability of on-farm activities, represented by an increase in π_f:

7 $$\partial o^*/\partial\pi_f = -(\partial^2 CE/\partial o\partial\pi_f)/(\partial^2 CE/\partial o^2) = 1/-n^{-1}r[1+(n-1)\rho]\sigma_k^2 < 0$$

Next, we investigate how optimal off-farm labor allocation changes due to a shift in the perceived riskiness of on-farm production activities. In our example, we expect this to be caused by the experience of a flood event[5], so an increase of σ_k^2. Thus, experiencing an extreme event is assumed to lead to a change in the subjective risk from agricultural production (e.g. Menapace et al., 2013).

A higher (perceived) riskiness of the on-farm production leads to an increase in the optimal off-farm labor allocation:

8 $$\partial o^*/\partial\sigma_k^2 = -(\partial^2 CE/\partial o\partial\sigma_k^2)/(\partial^2 CE/\partial o^2) = -n^{-1}r(L-o)[1+(n-1)\rho]/-n^{-1}r[1+(n-1)\rho]\sigma_k^2 > 0$$

This finding also allows us to account for differences across farms with respect to the production risks, e.g. due to differences in climate variability.

The above presented setup can also be used to identify potential differences across farms with respect to their adaptation behavior. For instance, we expect adaptation reactions to differ with farm size. More specifically, larger farms are expected to have a better return-risk ratio, for instance, due to better on-farm risk coping opportunities (Blank and Erickson 2007). Larger farms are also expected to have better access to risk-management strategies (e.g. credit reserves) as well as better management ability in dealing with risks (Poon and Weersink 2011; Velandia et al. 2009). Furthermore, larger farms are usually able to produce with lower risks because production risks are not perfectly correlated across space and larger acreages thus have an on-farm risk reducing effect (e.g. Marra and Schurle 1994). One possibility to express those properties of larger farms may be expressed as decrease in the variance of the on-farm production, so equation 8 can be used to show that off-farm labor allocation is decreasing with decreasing riskiness of on-farm production. Another way to depict effects of larger farm size, is to investigate the effect of better on-farm hedging effectiveness, i.e. a decrease in ρ, on off-farm labor allocation:

9 $$\partial o^*/\partial-\rho = (\partial^2 CE/\partial o\partial\rho)/(\partial^2 CE/\partial o^2) = n^{-1}r(L-o)(n-1)\sigma_k^2/-n^{-1}r[1+(n-1)\rho]\sigma_k^2 < 0$$

It shows that a better on-farm hedging effectiveness leads to lower provision of labor resources for off-farm activities. In summary, we thus expect larger farms to work less off the farm[6].

Moreover, optimal off-farm labor allocation is decreasing in the level of on-farm diversity:

[5] We, however, assume not necessarily a change in the expected returns because we assume that the occurrence of a flood event is inducing only a change in the subjective probability. In contrast, we do not assume a change in the actual underlying (objective) probability distribution of flood occurrence. Taking also aspects of transitory changes in climate risks into account could be a useful extension of this research related to changes in the occurrences of extreme events due to climate change.

[6] Along these lines, larger farms are also expected to react to a smaller extent to increases in risks.

10 $\partial o^*/\partial n = -(\partial^2 CE/\partial o \partial n)/(\partial^2 CE/\partial o^2) = n^{-2} r(L-o)\sigma_k^2[1-\rho]/{-n^{-1}} r[1+(n-1)\rho]\sigma_k^2 < 0$

Thus, on- and off-farm risk management strategies are interrelated. In particular, on-farm risk management measures lead to a lower use of risk management actions taken off the farm.

2.3. On-farm diversity

Next, we investigate the optimal diversity of the on-farm portfolio (expressed by the number of activities n). In this situation, the marginal costs of diversity must be equal to the marginal risk premium at this diversity level, which represents the benefits for the farmer arising from an additional diversification[7]:

11 $\partial CE/\partial n = -c(n) - n\partial c(n)/\partial n + 0.5n^{-2} r(L-o)^2[1-\rho]\sigma_k^2 = 0$

Again, we can use the implicit function theorem to derive inferences from our theoretical model. First, we can show that optimal on-farm diversification increases with the perceived riskiness of on-farm activities:

12 $\partial n^*/\partial \sigma_k^2 = -(\partial^2 CE/\partial n \partial \sigma_k^2)/(\partial^2 CE/\partial n^2) = \{-0.5n^{-2} r(L-o)^2[1-\rho]\}/\{-2\partial c(n)/\partial n - n\,\partial^2 c(n)/\partial n^2 - n^{-3} r(L-o)^2[1-\rho]\sigma_k^2\} > 0$

It shows that in response to a higher subjective portfolio risk, the farmer chooses a more diverse and less risky portfolio, which also reduces his expected return (because $\partial c(n)/\partial n > 0$). Thus, the risk-averse farmer gives up some of his profit to cope with increasing risks[8] (e.g. Iglesias et al., 2012).

Recalling our above presented analysis with respect to the expected effects of larger farm size, equation 12 also shows that farms facing lower on-farm risk will use less diverse portfolios. In contrast, a better on-farm hedging effectiveness of larger farms leads to higher diversification levels chosen on the farm:

14 $\partial n^*/\partial - \rho = (\partial^2 CE/\partial n \partial \rho)/(\partial^2 CE/\partial n^2) = \{-\frac{1}{2} n^{-2}(L-o)^2\sigma_k^2\}/\{-2\partial c(n)/\partial n - n\,\partial^2 c(n)/\partial n^2 - n^{-3} r(L-o)^2[1-\rho]\sigma_k^2\} > 0$

Thus, the expected effect of farm size on optimal diversification is ambiguous. Furthermore, optimal on-farm diversification increases with increasing risk aversion:

13 $\partial n^*/\partial r = -(\partial^2 CE/\partial n \partial r)/(\partial^2 CE/\partial n^2) = \{-0.5n^{-2}(L-o)^2[1-\rho]\sigma_k^2\}/\{-2\partial c(n)/\partial n - n\,\partial^2 c(n)/\partial n^2 - n^{-3} r(L-o)^2[1-\rho]\sigma_k^2\} > 0$

Finally, we can show that also on-farm diversification is affected by the level of off-farm labor allocation:

15 $\partial n^*/\partial o = -(\partial^2 CE/\partial n \partial o^*)/(\partial^2 CE/\partial n^2) = \{n^{-2} r(L-o)[1-\rho]\sigma_k^2\}/\{-2\partial c(n)/\partial n - n\,\partial^2 c(n)/\partial n^2 - n^{-3} r(L-o)^2[1-\rho]\sigma_k^2\} < 0$

Equation 15 thus shows that the optimal level of diversification decreases if more risk-free income is generated from off-farm allocation of labor. In summary, our results from the

[7] Recall that we assumed advantages of diversification for the farmer to solely stem from its risk reduction property.

[8] Due to the spatial immobility of land resources, complete flood risk avoidance due to relocation is not possible for farmers. In contrast, house owners have been found to have a substantial willingness to pay to elevate a new house in order to be safe to flooding (Botzen et al. 2013).

theoretical model thus reveal two contrary paths how farmers may react to higher subjective on-farm risks after experiencing a flood event: A) Farmers choose less risky portfolios. B) Farmers react by increasing the riskiness of their on-farm activities by decreasing diversification. Such choice, however, will be accompanied by an increase of the involvement in off-farm employment. Thus, not considering farmers' off-farm opportunities may lead to erroneous expectations how farmers react to changes in the riskiness of agricultural production due to the occurrence of flood events.

3. Empirical Framework

To test the empirical validity of our hypotheses derived above we employ microeconometric modeling to estimate different functional relationships with respect to risk related farm behavior. Especially we are interested in the potential effects of flooding related characteristics on off-farm labor allocation and on-farm diversity decisions controlling for a variety of financial, economic, policy, climatic, spatial as well as individual farm conditions. The formal models we estimate can be described as

16 $$y_{it} = f(\boldsymbol{x}_{it}\beta)$$

with the subscripts relating to farm i at time t, y as the production behavior related indicator and **x** as a vector of a variety of different factors. We expect that farmers' production choices are significantly driven by relative price developments in previous periods (reflecting price expectations for the current period), policy changes but also significantly by climate conditions and input quality differences. Further, previous production decisions (y_{it-1}) might be relevant for current production choices and plans (e.g. representing adjustment costs for restructuring farm plans). Beside stochastic influences (ϵ_{it}) also unobserved individual farm effects (u_i) play a role in explaining variation in production decisions across farms and time. Hence, the simple model in (16) can be revised leading to a dynamic specification

17 $$y_{it} = f(y_{it-1}\gamma + \boldsymbol{x}_{it}\beta + u_i + \epsilon_{it})$$

for i = {1,…,N} and t = {1,…,T}. Applying an OLS estimator on (17) would lead to biased and inconsistent results as the lagged regressor is also a function of ϵ_{it}. A fixed-effects estimator would be the natural choice when allowing for individual effects. However, Nickell (1981) showed that this estimator would lead to biased estimates as the lagged regressor would be correlated with the individual farm effects u_i. Based on the notion that an instrumental variables approach (Anderson and Hsiao 1981) would not exploit all of the information available in the data sample, Arellano and Bond (1991) proposed an alternative but efficient estimation procedure for the estimation of such dynamic problems. They note that in a Generalized Method of Moments (GMM) context one may construct more efficient estimates of the dynamic panel data model. The Arellano-Bond estimator, hence, sets up a generalized method of moments (GMM) problem in which the model is specified as a system of equations, one per time period, where the instruments applicable to each equation can differ. Blundell and Bond (1998) suggest making use of additional level information to overcome problems with weak instruments. The combination of moment restrictions for differences and levels results in an estimator labeled as GMM-system-estimator by Arellano and Bond (see also Arellano and Bover 1995). Here, additional moment conditions are used in which lagged differences of the dependent variable are orthogonal to levels of the disturbances. We apply this GMM based system estimator on the dynamic equation described in (17) where the GMM-system-estimator exploits T-2 orthogonality restrictions in levels (see also e.g. Behr 2003). Observation t in levels

18 $$y_{it} = y_{it-1}\gamma + \boldsymbol{x'}_{it}\beta + u_i + \epsilon_{it}$$

is used for estimation and differences are used as valid instruments. If we consider the last observation T

19 $$y_{iT} = y_{iT-1}\gamma + \boldsymbol{x'}_{iT}\beta + u_i + \epsilon_{iT}$$

and use the corresponding instruments are $dy_{i1}, dy_{i2}, dy_{iT-1}, dx'_{i1}, dx'_{i2}, dx'_{iT}$. Estimation of the instrumented equation is based on the following matrices

20 $$y_i = \begin{bmatrix} y_{i3} - y_{i2} \\ y_{i4} - y_{i3} \\ \dots \\ y_{iT} - y_{iT-1} \\ y_{i3} \\ \dots \\ y_{iT} \end{bmatrix} \quad X_i = \begin{bmatrix} y_{i2} - y_{i1} & x'_{i3} - x'_{i2} \\ y_{i3} - y_{i2} & x'_{i4} - x'_{i3} \\ \dots & \dots \\ y_{iT-1} - y_{iT-2} & x'_{iT} - x'_{iT-1} \\ y_{i2} & x'_{i2} \\ \dots & \dots \\ y_{iT-1} & x'_{iT} \end{bmatrix}$$

with the explanatory variables X, the parameters to be estimated θ and the instruments W as follows

21 $$\hat{X} = (y_{-1}, X),\ \ \theta' = (\gamma, \beta'),\ \ W = (W_1', W_2', \dots, W_N')'$$

The lagged instruments' W_i^L matrix and the differenced instruments' W_i^D matrix is given by

22 $$W_i^L = \begin{bmatrix} [y_{i1}, x'_{i1}, x'_{i2}] & 0 & \dots & 0 \\ 0 & [y_{i1}, y_{i2}, x'_{i1}, x'_{i2}, x'_{i3}] & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & [y_{i1}, y_{i2}, \dots, y_{iT-2}, x'_{i1}, x'_{i2}, \dots, x'_{iT-1}] \end{bmatrix}$$

23 $$W_i^D = \begin{bmatrix} [dy_{i2}, dx'_{i1}, dx'_{i3}] & 0 & \dots & 0 \\ 0 & [dy'_{i2}, dy'_{i3}, dx'_{i2}, dx'_{i3}, dx'_{i4}] & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & [dy'_{i2}, \dots, dy'_{iT-2}, dx'_{i2}, \dots, dx'_{iT-1}] \end{bmatrix}$$

combining to the overall matrix of the instruments used in estimation s follows

24 $$W_i = \begin{bmatrix} W_i^D & 0 \\ 0 & W_i^L \end{bmatrix}$$

The first-step estimator is then

25 $$V = W'JW = \sum_{i=1}^{N} W_i' J_T W_i$$

with $J = (I_N \otimes J^{DL\prime})$ and $J^D = \begin{bmatrix} 2 & -1 & \dots & 0 \\ -1 & 2 & \dots & \dots \\ \dots & \dots & \dots & -1 \\ 0 & \dots & -1 & 2 \end{bmatrix}$, $J^L = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & \dots \\ \dots & \dots & \dots & 0 \\ 0 & \dots & 0 & 1 \end{bmatrix}$, and

$J^{DL} = \begin{bmatrix} W_i^D & 0 \\ 0 & W_i^L \end{bmatrix}$. The second-step GMM estimator (see also White 1980) is then

26 $$\hat{V} = \sum_{i=1}^{N} W_i{}' J_T \hat{\varepsilon}_i \hat{\varepsilon}'_i W_i \ .$$

The resulting final estimator can be denoted as

27 $$\hat{\tau}^{GMM-SYS} = \left(XW\hat{V}^{-1}W'X\right)^{-1} X'W\hat{V}^{-1}W'y.$$

As dependent variables we use either off-farm income (model I) or an on-farm diversity index (model II) for each farm and year[9]. Explanatory variables are discussed in detail in the data section.

4. Case Study and Data

The UK has been among those EU countries mostly affected by flooding in the last 20 years. Currently, over 5 million people in England and Wales live and work in properties that are at risk of flooding from rivers or the sea (Environment Agency 25/01/2011). The most common forms of floods in the UK are river flooding, coastal flooding, surface water flooding, sewer flooding and groundwater flooding. The devastating impact of flooding was demonstrated during the summer 2007 floods in Yorkshire and the Midlands. During these floods 14 people lost their lives, 7,000 people were rescued from flood waters by emergency services and 55,000 properties were flooded. The floods also resulted in a cost of £3 billion to the insurance industry. Whilst the focus of attention was placed on the impact on life and urban property, an estimated 42,000 hectares of farmland were significantly affected by flooding, especially in floodplain areas. As a land-based industry, agriculture is vulnerable to both surface and groundwater flooding and is particularly vulnerable in the summer period when crops are nearing harvest and grassland for livestock is most productive (Huber, 2004, Posthumus et al. 2009). Floods can cause losses of physical production and infrastructure, reductions of the quality of agricultural products and can have long-term impacts on farm production by affecting soil conditions (Merz et al. 2010). Based on survey data and derived cost estimates Posthumus et al. (2009) report total costs of about 1% of the gross value added for the agricultural industry in England due to the flooding in 2007. These estimates relate to costs of flood damage at farm level including damage to property, loss of expected income and increased costs directly attributable to flooding. These include also the imputed cost of increased family labor. Most of these costs were uninsured as they related to loss of expected income from crops and livestock production rather than damage to property.

Given its relevance, policymakers are becoming increasingly concerned about flooding and flood risk management. Tobin and Montz (1997) have impressively outlined the tied relationship between flood disasters and the demand by the public for a policy response. Parker (2000) argues that it takes a severe and damaging flood to place flooding on the political agenda, at a time when the public and media response is such that a failure to act is politically unacceptable. Johnson et al (2005) identify three key phases of incremental flood

[9] Off-farm income is measured in relative terms, i.e. per ha.

policy change since World War II: land drainage, flood defense and, most recently, flood risk management. Each of these phases reflects a changing set of beliefs, values and attitudes towards the flood problem, which in turn influences attitudes towards structural flood defenses, flood warning systems, public awareness raising, land use planning and development control for flood risk areas. Relevant policies introduced in the UK or at the EU level have been: the UK improvement and modification of flood warning systems in 1998, the EU Water Framework Directive (WFD) in 2000, the UK Floodline Warnings Directive (FWD) in 2004, the UK Planning Policy Guidance (PPG) in 2006, the EU Floods Directive in 2007, the Pitt report in 2008, and the recent Flood and Water Management Act (FWM) in October 2010. The requirements of the EU Floods Directive have been met by the UK with the Flood Risk Regulations 2009. The Directive requires member states to develop and update a series of tools for managing all sources of flood risk, in particular: preliminary flood risk assessments (PFRAs), flood risk and flood hazard maps, flood risk management plans, co-ordination of flood risk management at a strategic level, improved public participation in flood risk management, and co-ordination of flood risk management with the WFD. The UK Flood and Water Management Act 2010 aims to create a more effective means of managing the risk of flood and coastal erosion in the UK. It sets out which bodies are responsible for managing flood risk with the Environmental Agency as the lead competent authority (HM Government 2010). Based on the relevant literature on UK flood impacts we focus in the subsequent empirical analysis on the most relevant flood related policy measures as those introduced or applied in the years 1998, 2007 and 2010 (see e.g. Posthumus et al. 2009).

The dataset we use for estimation purposes relates to flooding events in the UK for the period 1990 to 2011. Farm production data from the UK Farm Business Survey (Farm Robust Type 1 ‘cereals’ and 2 ‘general cropping’) has been obtained for this period. We augment this production and socioeconomic data by altitude and soil quality related data[10] as well as temperature and precipitation related information based on datasets made available by the UK Met Office.[11] Further, individual flood event related data is used based on statistics released by the Dartmouth Flood Observatory.

To represent on-farm production diversity we construct a diversity index based on a Herfindahl type indexation with the nominator containing the sum of squared incomes related to potatoes, vegetables, sugar beet, cereals, (remaining) crops, dairy and livestock[12] whereas the denominator is the squared total farm income. To ensure that increasing diversification is reflected by higher index realizations, we use a Gibbs-Martin index (i.e. 1- the Herfindahl index). This index ranges from 0 to 1, values close to 0 indicate a high degree of specialization. The degree of financial liquidity of the individual farm is measured by one minus the ratio fixed to total assets which means that low values of the ratio indicate a low degree of liquidity (corresponding to a high degree of illiquidity).

Finally, the occurrence and severeness of the flooding events experienced by the individual farm in the respective year is measured by an ordered indicator based on the multiplication of a binary variable for the flooding event actually occurring or not, and an ordered event severeness variable taking the values 1 for minor, 2 for medium and 3 for major severeness of the flooding event. The categorization of the individual events follows the constantly updated

[10] Also based on the UK Farm Business Survey (see also www.farmbusinesssurvey.co.uk).
[11] The UK Met Office: http://www.metoffice.gov.uk/climate/uk/datasets/ (minimum and maximum temperatures which are used to construct a mean temperature, sunshine hours, mm rainfall, raindays per year and region: East/NorthEast, NorthWest, Midlands, EastAnglia, SouthWest, SouthEast).
[12] This index has been chosen because next to the number of activities also their relative shares in the portfolio are important if profits are not equal.

flood statistics released by the Dartmouth Flood Observatory[13]. It is important to highlight that in particular the lagged effects of floods are relevant for our analysis. This is due to the fact that we expect actual adaptation responses, such as use of different crops or re-allocation of labor resources, to take place in the next agricultural season. Table 1 gives a descriptive summary of the data sample.

In our econometric models we include one lag of the dependent variable (off-farm income or on-farm diversity) as a regressor and model as strictly exogenous regressors the following variables: the one-period lagged price for crops, the one-period lagged price for general agricultural inputs, the one-period lagged regional wage index, agricultural policy indicators for the years 1992, 2000 and 2003, flood policy indicators for the years 1998, 2007 and 2010[14], a farm size indicator, the organizational form of the farm business, altitude of the farm holding, and an indicator if the farm is located in a less-favored area.[15] To enable the observation of non-linear effects of the farmers' age on off-farm and diversity related decisions (e.g. Serra et al., 2005), we include age as linear and quadratic terms in our analysis. Furthermore, standard deviations of mean temperature, the number of sunshine hours, precipitation in mm and the number of rain days measured at the regional level and for the entire time period considered (1990-2011) are included in the model to account for the general climatic variability and thus production risks a farm faces.

Further we model the following variables as endogenous regressors[16]: an ordered flooding occurrence and severeness indicator[17], interaction terms of the flooding indicator with farm diversity, off-farm income and farm size (depending on the model), a financial liquidity index, the share of output subsidies in total farm income (direct quantity of produce related subsidies), the diversity index (in the off-farm model), and the share of off-farm income in total income (in the diversity model). We also incorporate one-period lagged regressors of all endogenously determined variables. To capture finally the effect of nonlinear interactions between the size of the farm's operations and the flood occurrences, we further include a corresponding interaction term and its one-period lagged observation as exogenous regressor.

As instruments for the endogenously determined regressors all exogenous independent variables are used following the logic of the estimator applied. To ensure the robustness of our estimates we compute the bootstrapped bias-corrected standard errors and test for the quality of the chosen instruments by using appropriate test formulas (see e.g. Bowsher 2002).

[13] Flood data has been obtained at http://www.dartmouth.edu/~floods/Archives/index.html. A list of considered flood events can be obtained from the authors upon request.

[14] Flooding policy: 1998 – UK improvement and modification of flood warning system and general public awareness rise; 2007 – EU Floods Directive; 2010 – Flood Water Management Act.

[15] The business form is categorized as follows: 1 – sole trader, 2 – partnership (family), 3 – partnership (other), 4 – farming company, 5 – other. Altitude: 1 - most of holding below 300m, 2 – most of holding at 300m to 600m, 3 – most of holding at 600m or over; LFA codes: 1 – all land outside LFA, 2 – all land inside SDA, 3 – all land inside DA, 4 - 50%+ in LFA of which 50%+ in SDA, 5 - 50%+ in LFA of which 50%+ in DA, 6 - <50% in LFA of which 50%+ in SDA, 7 - <50% in LFA of which 50%+ in DA.

[16] Such regressors that are potentially correlated with unobservables relegated to the error term of the model.

[17] Flooding occurrence and severeness indicator is defined as follows: 0 - farm experiences no floodings in the respective year; 1 – experience of large flood event (defined by significant damage to structures or agriculture, fatalities, and/or 1-2 decades-long reported interval since the last similar event); 2 – experience of very large event (defined by greater than 20 yr but less than 100 year recurrence interval, and/or a local recurrence interval of at 10-20 yr); 3 - experience of extreme event (defined by an estimated recurrence interval greater than 100 years. Average severity of flooding events per year if more than one event) Source: http://www.dartmouth.edu/~floods/Archives/index.html.

Table 1. Descriptive Statistics Sample 1990 – 2011.

Variable	**Mean (SD)**
Total income (in GBP)	267837.4 (346703.7)
Off-farm income (in GBP)	5126.5 (11040.2)
Diversity index (continuous: 0 to 1)	0.567 (0.232)
Chemical expenditure (in GBP)	17723.9 (22719.3)
Variable input expenditure (in GBP)	59763.5 (80771.3)
Rainfall (in mm)	823.595 (239.674)
Days of rainfall	129.795 (20.473)
Hours of sunshine	1537.644 (144.851)
SD of mean temperature (in °Celsius)	0.465 (0.021)
SD of rainfall (in mm)	124.557 (23.299)
SD of days of rainfall	13.538 (1.192)
SD of hours of sunshine	114.391 (6.712)
Crop price index	126.548 (22.554)
General input price index	113.846 (22.068)
Financial liquidity index	0.203 (0.188)
Output subsidies as share of income	0.111 (0.101)
Flooding indicator (discrete: 1 to 3)	0.207 (0.676)
Agricultural policy indicator 1 (1992)	0.936 (0.244)
Agricultural policy indicator 2 (2000)	0.539 (0.498)
Agricultural policy indicator 3 (2003)	0.378 (0.485)
Flood policy indicator 1 (1998)	0.648 (0.476)
Flood policy indicator 2 (2007)	0.199 (0.399)
Flood policy indicator 3 (2010)	0.072 (0.258)
Size category (discrete: 1 to 3)	2.428 (0.704)
Age of farmer (in years)	54.459 (65.062)
Business form (discrete: 1 to 5)	1.848 (0.942)
Altitude of holding (discrete: 1 to 3)	0.845 (0.373)
Less favoured area indicator (LFA) (discrete: 1 to 7)	1.081 (0.624)

Based on 13745 observations. Prices are deflated to base year 1980 using Eurostat indices. Standard deviation is given in brackets. The business form is categorized as follows: 1 – sole trader, 2 – partnership (family), 3 – partnership (other), 4 – farming company, 5 – other. Altitude categories: 1 - most of holding below 300m, 2 – most of holding at 300m to 600m, 3 – most of holding at 600m or over; LFA indicator codes: 1 – all land outside LFA, 2 – all land inside SDA, 3 – all land inside DA, 4 - 50%+ in LFA of which 50%+ in SDA, 5 - 50%+ in LFA of which 50%+ in DA, 6 - <50% in LFA of which 50%+ in SDA, 7 - <50% in LFA of which 50%+ in DA.

5. Results and Discussion

All estimated models show a good overall statistical significance, the majority of relevant variables are estimated at a satisfactory significance level. The moment conditions of the dynamic panel data estimator used are only valid if there is no serial correlation in the idosyncratic errors. The Arellano-Bond test results confirm that this assumption holds for all models estimated (i.e. the tests fail to reject the null hypothesis of valid moment conditions). Further, the dynamic estimator produces only valid results if the overidentifying moment conditions are valid. The applied Sargan test results do not provide strong evidence against the null hypothesis of overidentifying restrictions. Hence, we conclude that the chosen estimation strategy including the choice of instruments is efficient and valid (Tables 2 and 3).

Off-farm income (Model I, Table 2). We find that the flood indicator has a negative effect on off-farm income in the year of flood occurrence. This may indicate some peak in on-farm workload at the time of the flood (e.g. to prevent higher damages) or directly after the flood occurrence (e.g. cleaning up, preparing re-seeding). In contrast, we found a higher off-farm income in the year after the flood occurrence, showing the expected switch towards the riskless asset after the experience of a flood event. The interaction term between farm size and the flood indicator variable results in an opposing effect compared to the sign of the coefficient by the flood indicator variable. This indicates that larger farms show less emphasized adjustment behavior after the flood occurrence with respect to their off-farm employment. Furthermore, our results indicate that larger farms are generally characterized by lower (relative) off-farm incomes, which is in line with our findings from the theoretical model and earlier research (e.g. Bell 2011; Mishra and Goodwin 1997; Poon and Weersink 2011; Serra et al. 2005).

We find a significant negative relationship between off-farm income and the diversity index. Thus, farms using a less diverse on-farm portfolio (indicated by a lower diversity index) are stronger involved in off-farm activities. This underlines our hypothesis that off-farm employment and on-farm diversity strategies are substitutes for the farmer. Furthermore, also crop- and input prices are found to affect the level of off-farm employment chosen by the farmer. More specifically, an increase in the one year lagged crop price (input price) index leads to a decrease (increase) in off-farm activities. Thus, increasing on-farm income opportunities decrease the attractiveness of off-farm employment and vice versa, which is consistent with our developed hypothesis and findings of previous research (e.g. Serra et al. 2005; Woldehanna et al. 2000). Along these lines, we also find evidence supporting our hypothesis of a positive effect of the regional wage level on off-farm allocation of labor resources. Further, our results show that with an increasing share of assets of the farm being fixed (a lower liquidity index), involvement in off-farm activities is decreasing. This could indicate that once investments, potentially with a quasi-sunk character, have been made, on-farm use of labor resources reacts less to changes in other factors determining off-farm activities.

The estimated coefficient for the organizational form of the farm business indicates that the more commercialized the farm business is (i.e. the less family farm type structural characteristics play a role) the lower is the importance of off-farm activities. The latter effect is also captured by the estimated negative effect of the size of the farm business on off-farm income. No significant effect of the factor age was found.

Finally, we found a strong positive and significant effect of the standard deviations of the climate variables. This confirms the conjecture that weather fluctuations increase the riskiness of on-farm activities, hence, triggers the use of risk-free off-farm activities (e.g. Serra et al. 2005).

Our results further suggest that flood policy measures significantly affected the depth of off-farm employment. We find that the improvement and modification of the UK flood warning system in 1998 in conjunction with measures focusing on a general public awareness rise towards flooding led to a higher importance of off-farm activities. On the other hand, the UK Flood Water Management Act from 2010 negatively affected the level of off-farm activities, which could be due to a significant increase in trust by farmers towards the effectiveness of revised flood prevention systems. Finally, EU agricultural policy revisions show an effect only for the reform in 2000 (Agenda 2000) which obviously led a lower need for off-farm income, e.g. via increased compensation payments. Along these lines, a larger share of subsidization to total income is found to reduce off-farm employment. These results are in line with earlier research showing that the use of risk management strategies decreases with increasing shares of non-volatile support payments (Finger and Lehmann 2012; Hennessy 1998).

Table 2. System-Dynamic Panel Data Estimates - Off-Farm Income

Variable	Coefficient	Robust Standard Error [1]
I) Lagged		
Off-farm income per ha (lag t-1)	0.246***	0.011
II) Exogenous		
Crop price index (lag t-1)	-0.878***	0.098
General input price index (lag t-1)	0.701***	0.129
Regional wage index (lag t-1)	0.196***	0.037
Agricultural policy indicator 1992	1.942	4.455
Agricultural policy indicator 2000	-32.045***	3.344
Agricultural policy indicator 2003	-4.041	3.021
Flood policy indicator 1998	19.853***	3.461
Flood policy indicator 2007	2.984	3.543
Flood policy indicator 2010	-19.919***	3.422
Farm size class	-23.813***	2.296
Age of farmer	0.154	0.269
Age * Age	-8.61e-05	1.32e-04
Business form	-18.059***	4.293
Altitude	-30.277***	8.821
Less favoured area	-3.613	7.382
Standard deviation of mean temperature	7932.091***	1004.284
Standard deviation of hours of sunshine	0.964***	0.554
Standard deviation of rainfall	5.131***	0.656
Standard deviation of days of rain	50.351***	6.757
Farm size * flood indicator	10.653***	2.645
Farm size * flood indicator (lag t-1)	-5.726**	2.414
III) Endogenous [4]		
Flood indicator	-29.673***	6.741
Flood indicator (lag t-1)	15.457**	6.228
Diversity index	-193.379***	8.158
Diversity index (lag t-1)	-32.511***	7.995
Liquidity index	52.067***	17.351
Liquidity index (lag t-1)	64.095***	17.561
Output subsidies share of total income	-107.049***	18.376
Output subsidies share of total income (lag t-1)	43.377***	16.534
Constant	-1584.446***	255.587
IV) Model Statistics and Diagnostics		
Number of observations	11078	
Number of groups	1734	
Number of instruments	1600	
Wald chi2(36)	2922.68***	
Sargan test statistic [2]	700.207	
Arellano-Bond test statistic [3]	1: -0.3675, 2: 0.2409	

1: ***,**,*: significance at 1, 5, 10%-level; 2: Sargan test statistic of overidentifying restrictions; 3: Arellano-Bond test for zero autocorrelation in first-differenced errors. 4: Instruments for endogenously determined regressors: exogenous regressors under II).

Diversity of on-farm portfolio (Model II, Table 3). The flood indicator has a negative coefficient in the on-farm portfolio diversity model for the year of the flood occurrence, indicating a reduction in diversity. This result is caused by non-uniform effects of the flood occurrence on different activities of the farm. For instance, crop production may be (in terms of direct impacts) more likely to be affected by a flood than dairy production. Given the Herfindahl type definition of our diversity index, this asymmetry causes a decreasing index in the short-run, particularly in the setting of the here analyzed farm with particular focus on crop production. More important for our analysis, the lagged effect of the flood indicator shows that the diversity of the on-farm portfolio increases in flood occurrence (and intensity) in the subsequent period. Thus, choosing a more diverse and thus less risky portfolio seems to be – at least for some farmers – an optimal long-term response to cope with higher risks. The delay of this response is expected to be caused by the fact that resource allocation decisions (e.g. on land use) are taken on an annual basis, so that changes in on-farm portfolios may not be realizable within the year of flood occurrence. Also in this model, we find the interaction terms between farm size and the flood indicator variable results to have opposing effects compared to the sign of the coefficient by the flood indicator variable alone. Thus, larger farms show a less emphasized adjustment behavior after the flood occurrence also with respect to changes in on-farm diversity. However, larger farms are found to be more diversified. These findings underline the ambiguous expectations on the farm size effects on diversification derived above.

The interaction term between off-farm income and the flood indicator variable has a positive coefficient. This underlines the above found pattern that in the year of flood occurrence, both off-farm employment and on-farm diversity tend to be increased. More importantly, considering the interaction of flood occurrence and the (one year) shifted response in off-farm income, we find that off- and on-farm risk management strategies are used as substitutes. Thus, if a farm increases off-farm employment in response to flood occurrence, a less diverse (i.e. more risky) on-farm strategy is chosen by the farmer. More general, the results show that farms with higher off-farm employment are characterized by less diverse on-farm portfolios, which confirms our hypothesis and is consistent with earlier research (e.g. Blank and Erickson 2007).

Furthermore, we found a positive and significant effect of the standard deviations of the climate variables (except for sunshine hours). Thus, farmers operating under more variable climate conditions tend to choose more diverse on-farm portfolios to cope with these risks, which is in line with other empirical research (e.g. Bezabih and Sarr 2012). A negative but saturating relationship between the on-farm diversity index and farmers' age has been found, indicating younger farmers to use more diverse on-farm portfolios. We find chosen levels of diversification to be smaller (larger) if output (input) prices are high. Thus, a higher profitability of on-farm activities triggers specialization responses and vice versa.

Flood policy measures significantly affected the level of diversity. We find that the improvement and modification of the UK flood warning system in 1998 in conjunction with measures focusing on a general public awareness rise towards flooding led to a higher diversity of farm production activities. The same significant effect has been found for the EU Floods Directive implemented in 2007. However, the UK Flood Water Management Act from 2010 shows to negatively affect the level of diversity which could be due to a significant increase in trust by farmers towards the effectiveness of revised flood prevention systems. These findings are generally in line with those estimated for the importance of off-farm income, which holds also with respect to EU agricultural policy revisions represented by the agricultural policy indicator variables. Here, again we find only a significant effect with respect to Agenda 2000 leading to a lower diversity of farm activities.

Table 3. System-Dynamic Panel Data Estimates – Diversity Index

Variable	Coefficient	Robust Standard Error [1]
I) Lagged		
Diversity index (lag t-1)	0.0811***	0.011
II) Exogenous		
Crop price index (lag t-1)	-0.002***	2.22e-04
General input price index (lag t-1)	0.003***	2.79e-04
Agricultural policy indicator 2000	-0.042***	0.006
Agricultural policy indicator 2003	0.007	0.006
Flood policy indicator 1998	0.062***	0.007
Flood policy indicator 2007	0.019***	0.007
Flood policy indicator 2010	-0.048***	0.007
Farm size class	0.014**	0.006
Age of farmer	-0.002***	5.76e-04
Age * Age	8.59e-07***	2.38e-07
Business form	0.004	0.009
Less favoured area	-0.004	0.014
Altitude	-0.101***	0.019
Standard deviation of mean temperature	4.926**	2.418
Standard deviation of hours of sunshine	-0.002*	0.001
Standard deviation of rainfall	0.003**	0.001
Standard deviation of days of rain	0.011	0.017
III) Endogenous [4]		
Flood indicator	-0.042***	0.014
Flood indicator (lag t-1)	0.141***	0.016
Off-farm income per ha	-6.87e-04***	1.05e-04
Off-farm income per ha (lag t-1)	3.08e-04***	6.46e-05
Liquidity index	-0.071*	0.036
Liquidity index (lag t-1)	0.076**	0.038
Output subsidies share of total income	-0.558***	0.039
Output subsidies share of total income (lag t-1)	0.201***	0.036
Off-farm income * flood indicator	4.62e-07***	4.96e-07
Off-farm income * flood indicator (lag t-1)	2.00e-07	5.01e-07
Off-farm income year after flood event	-6.67e-04***	1.02e-04
Off-farm income year after flood event (lag t-1)	-5.22e-05	6.18e-05
Farm size * flood indicator	0.015***	0.005
Farm size * flood indicator (lag t-1)	-0.046***	0.006
Constant	0.068	0.605
IV) Model Statistics and Diagnostics		
Number of observations	9129	
Number of groups	1517	
Number of instruments	1700	
Wald chi2(36)	1756.30***	
Sargan test statistic [2]	310.385	
Arellano-Bond test statistic [3]	1: -1.7429, 2: 0.2624	

1: ***,**,*: significance at 1, 5, 10%-level; 2: Sargan test statistic of overidentifying restrictions; 3: Arellano-Bond test for zero autocorrelation in first-differenced errors. 4: Instruments for endogenously determined regressors: exogenous regressors under II).

6. Conclusions

We develop a conceptual and empirical framework to analyze farmers' adaptation responses to climate related extreme events. We extend earlier research by investigating measures taken at the whole farm level including on- and off-farm decisions as well as their interactions. Our empirical analysis focuses on the case of floods in UK agriculture and uses farm-level panel data for the period 1990-2011 enriched by a wide range of biophysical and climatic information. Dynamic panel models are estimated following a Arellano and Bover/Blundell and Bond GMM system approach, for off-farm income and the diversity of on-farm portfolios. In these models, the dynamic effects of flood occurrence and intensity as well as interactions between the dependent variables are estimated, by controlling for other biophysical, economic and farm specific variables.

The empirical analysis shows that on- and off-farm risk management are driven by farm and farmers' characteristics, climatic and economic boundary conditions as well as by agriculture an flood policies. For instance, off-farm employment and on-farm diversity are higher for farms facing more variable climatic conditions. Furthermore, increasing crop price levels lead to less off-farm employment and less diverse on-farm production. In contrast, both off-farm employment and diversity of on-farm production have been found to increase in input price levels. The use of risk management instruments both on- and off- the farm decreases with higher subsidy levels and were reduced with the introduction of the Agenda 2000 as well as the recent UK Flood Water Management Act.

We find that both off-farm employment and more diverse on-farm production are strategies used by farmers to respond after the occurrence of a flood. On- and off-farm strategies are, however, found to be partially mutually exclusive. If increasing off-farm employment is used as adjustment to higher risks, on-farm diversification is reduced. Thus, we find ambiguous on-farm risk adaptation responses depending on the use of off-farm risk management strategies. Furthermore, our results show that adaptation responses differ significantly by farm size. Larger farms show significantly smaller responses to flood events with regard to on-farm diversification and off-farm employment, which is, among others, due to the fact that they are characterized by better return-risk ratios and are thus less affected by an increase in perceived production risks.

Thus, our results underline the relevance of whole-farm level strategies to cope with climatic extreme events such as floods (e.g. Pivot and Martin 2002). This also implies that the (long-term) implications of such extreme events for farmers (e.g. Posthumus et al. 2009) should not be solely assessed in terms of on-farm performance (e.g. in terms of crop loss or yield reduction), but should account for both on- and off-farm resource use. A wide range of literature suggests that due to climate change extreme events are likely to occur more frequently in the future and agricultural production risks are expected to increase (e.g. Beniston et al. 2007; Gornall et al. 2010; Olesen et al. 2011). Against this background, our results suggest that higher risk due to climate change may not necessarily lead to more diverse production patterns (e.g. Bradshaw et al., 2004), an increase in risk reducing inputs (e.g. Smit and Skinner 2002) or, more general, an increased use of on-farm risk management. This is due to the fact that farms may also cope with higher risks by allocating assets outside of agricultural production. Thus, expectations that climate change may shift farmers towards more diverse (potentially more ecological valuable) production patterns (e.g. Lin 2011; Olesen et al. 2011) may be not generally valid. More general, tools that consider too narrow sets of adaptation responses could result in biased conclusions on climate change impacts and adaptation in agriculture.

Based on our analysis, future research should consider resource allocation opportunities off the farm to derive unbiased pictures of adaptation behavior. Thus, investigations on adaptation strategies in the framework of impact and vulnerability assessment as well as the development of policies supporting the management of climate risks should not be focused on on-farm strategies alone. The adaptation mechanisms revealed in our analysis are, however, only applicable if and only if other than on-farm opportunities are available to the farmer. This may, for example, not be the case in developing countries. An example is given by Devereux (2007) who show that floods in Malawi also cause disruptions beyond the agricultural sector and thus prevent applying the here outlined framework for adaptation. Finally, the microeconometric approach applied in this study shows that individual adaptation behavior with respect to extreme climate events can be robustly analyzed at individual farm level in an empirical setting.

References

Alem, Y., Bezabih, M., Kassie, M., & Zikhali, P. (2010). Does fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia. *Agricultural Economics*, 41(2), 165-175.

Anderson, T.W., & Hsiao, C. (1981). Estimation of Dynamic Models with Error Components. *Journal of the American Statistical Association*, 76, 598-606.

Anwar, M. R., Li Liu, D., Macadam, I., & Kelly, G. (2012). Adapting agriculture to climate change: a review. *Theoretical and Applied Climatology*, doi: 10.1007/s00704-012-0780-1

Arellano, M., & Bond, S.R. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies*, 58, 277-297.

Arellano, M., & Bover, O. (1995). Another Look at the Instrumental-Variable Estimation of Error-Components Models. *Journal of Econometrics*, 68, 29-52.

Behr, A. (2003). *A comparison of dynamic panel data estimators: Monte Carlo evidence and an application to the investment function*. Economic Research Centre. Deutsche Bundesbank. Discussion Paper 05/03.

Bell, R.A. (2011). Highly Optimized Tolerant (HOT) Farms in Rondônia: Productivity and Farm Size, and Implications for Environmental Licensing. *Ecology and Society*, 16(2), 7.

Beniston, M., D. Stephenson, D., O.B.Christensen, C. Ferro, C. Frei, S. Goyette, K. Halsnaes, T. Holt, K. Jyllhä, B. Koffi, J. Palutikof, R. Schöll, T. Semmler, & Woth, K. (2007). Future Extreme Events in European Climate: An Exploration of Regional Climate Projections. *Climatic Change*, 81, 71-95.

Berrang-Ford, L., Ford, J. D., & Paterson, J. (2011). Are we adapting to climate change? *Global Environmental Change*, 21(1), 25-33.

Bezabih, M., & Sarr, M. (2012). Risk Preferences and Environmental Uncertainty: Implications for Crop Diversification Decisions in Ethiopia. *Environmental and Resource Economics*, 53(4), 483-505.

Blank, S.C. (2001). Producers get squeezed up the farming food chain: A theory of crop portfolio composition and land use. *Review of Agricultural Economics*, 23(2), 404-422.

Blank, S.C., & Erickson, K.W. (2007). Agricultural household hedging with off-farm income. *Western Economics Forum*, Spring 2007, 1-13.

Blundell, R., & S. Bond (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics*, 87, 115-143.

Botzen, W.J.W., Aerts, J.C.J. H., & van den Bergh J.C.J.M. (2013). Individual preferences for reducing flood risk to near zero through elevation. *Mitigation and Adaptation Strategies for Global Change*, 18 (2), 229-244.

Bowsher, C. G. (2002). On testing overidentifying restrictions in dynamic panel data models. *Economics Letters*, 77, 211–220.

Bradshaw, B., Dolan, H., & Smit, B. (2004). Farm-level adaptation to climatic variability and change: crop diversification in the Canadian prairies. *Climatic Change*, 67(1), 119-141.

Bryan, E., Deressa, T. T., Gbetibouo, G. A., & Ringler, C. (2009). Adaptation to climate change in Ethiopia and South Africa: options and constraints. *Environmental Science & Policy*, 12(4), 413-426.

Chavas, J.-P. (2004). *Risk analysis in theory and practice*. San Diego: Elsevier.

Collender, R.N., & Zilberman, D. (1985). Land allocation under uncertainty for alternative specifications of return distributions. *American Journal of Agricultural Economics*, 67(4), 779-786.

Devereux, S. (2007). The impact of droughts and floods on food security and policy options to alleviate negative effects. *Agricultural Economics*, 37, 47-58

Di Falco, S., Penov, I., Aleksiev, A., & van Rensburg, T.M. (2010).Agrobiodiversity, farm profits and land fragmentation: evidence from Bulgaria. *Land Use Policy*, 27, 763–771.

Di Falco, S., Veronesi, M., & Yesuf, M (2011). Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia. *American Journal of Agricultural Economics*, 93(3), 829-846.

Ding, Y, Schoengold, K., & Tadesse, T. (2009). The Impact of Weather Extremes on Agricultural Production Methods: Does Drought Increase Adoption of Conservation Tillage Practices? *Journal of Agricultural and Resource Economics*, 34(3), 395-411.

Environment Agency (25/01/2011). http://www.environment-agency.gov.uk/homeandleisure/floods/default.aspx.

Finger, R., & Lehmann, N. (2012). The Influence of Direct Payments on Farmers' Hail Insurance Decisions. *Agricultural Economics*, 43(3), 343-354.

Goodwin, B.K. (2008). Climate variability implications for agricultural crop production and risk management: discussion. *American Journal of Agricultural Economics*, 90, 1263–1264.

Gornall, J.R., Betts, E., Burke, R., Clark, J., Willett, C.K., & Wiltshire, A. (2010). Implications of climate change for agricultural productivity in the early twenty-first century. *Philosophical Transactions of the Royal Society: Biological Sciences*, 365, 2973–2989.

Hall, J.W., Sayers, P.B., & Dawson, R. (2005). National-scale assessment of current and future flood risk in England and Wales. *Natural Hazards*, 36(1-2), 147–164.

Hennessy, D.A., 1998. The production effects of agricultural income support policies under uncertainty. *American Journal of Agricultural Economics*, 80(1), 46–57.

HM Government (2010). *Flood and Water Management Act 2010*. http://www.legislation.gov.uk/ukpga/2010/29/contents.

Huber, M. (2004). *Reforming The UK Flood Insurance Regime*. The Breakdown of a Gentlemen's Agreement. LSE CARR, Discussion Paper No. 18, London, UK.

Iglesias, A., Quiroga, S., Moneo, M., & Garrote, L. (2012). From climate change impacts to the development of adaptation strategies: challenges for agriculture in Europe. *Climatic Change*, 112(1), 143-168.

IPCC (2007). *Climate Change 2007: Impacts, Adaptation and Vulnerability*. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds., Cambridge: Cambridge University Press, 976pp.

Johnson, C.L., Tunstall, S.M., & Penning-Rowsell E.C. (2005). Floods as Catalysts for Policy Change: Historical Lessons from England and Wales. *Water Resources Development*, 21(4), 561–575.

Kyle, S.C. (1993). The relation between farm production risk and off-farm income. *Agricultural and Resource Economics Review,* 22, 179-88.

Lin, B.B. (2011). Resilience in agriculture through crop diversification: adaptive management for environmental change. *BioScience*, 61(3), 183-193.

Lobell, D.B., Schlenker, W. & Costa-Roberts, J. (2011). Climate Trends and Global Crop Production Since 1980. *Science*, 333(6042), 616-620.

Marra, M.C., & Schurle, B.W. (1994). Kansas wheat yield risk measures and aggregation: a meta-analysis approach. *Journal of Agricultural and Resource Economics*, 19(1), 69-77.

McNamara, K. T., & Weiss, C. (2005). Farm household income and on-and off-farm diversification. *Journal of Agricultural and Applied Economics*, *37*(1), 37-48.

Mechler, R., Hochrainer, S., Aaheim, A., Salen, H., & Wreford, A. (2010). Modelling economic impacts and adaptation to extreme events: Insights from European case studies. *Mitigation and Adaptation Strategies for Global Change*, 15(7), 737-762.

Menapace, L., Colson, G. & Raffaelli, R. (2013). Risk Aversion, Subjective Beliefs, and Farmer Risk Management Strategies. *American Journal of Agricultural Economics*, 95, 384-389.

Merz, B., Kreibich, H., Schwarze, R., & Thieken, A. (2010). Assessment of economic flood damage. *Natural Hazards and Earth System Sciences,* 10, 1697-1724.

Mishra A., & Goodwin B. (1997). Farm Income Variability and the Supply of Off-Farm Labor. *American Journal of Agricultural Economics,* 79, 880–887.

Mishra A., & Goodwin B. (1998). Income Risk and Allocation of Labour Time: An Empirical Investigation. *Applied Economics*, 30(12), 1549-1555.

Nickell, S.J. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica*, 49,1417-1426.

Olesen, J. E., Trnka, M., Kersebaum, K. C., Skjelvåg, A. O., Seguin, B., Peltonen-Sainio, P., Rossi, F., Kozyra, J. & Micale, F. (2011). Impacts and adaptation of European crop production systems to climate change. *European Journal of Agronomy*, 34(2), 96-112.

Orlove B. (2005). Human adaptation to climate change: a review of three historical cases and some general perspectives. *Environmental Science & Policy*, 8, 589–600.

Ortiz-Bobea, A., & Just, R.E. (2013). Modeling the Structure of Adaptation in Climate Change Impact Assessment. *American Journal of Agricultural Economics*, 95 (2), 244-251.

Parker, D.J. (Ed.) (2000). *Floods*. London: Routledge.

Pivot, J. M., & Martin, P. (2002). Farms adaptation to changes in flood risk: a management approach. *Journal of Hydrology,* 267(1), 12-25.

Poon, K., & Weersink, A. (2011). Factors affecting variability in farm and off-farm income. *Agricultural Finance Review,* 71(3), 379-397.

Popp, M., & Rudstrom, M. (2000). Crop Enterprise Diversification and Specialty Crops. *Agricultural Finance Review,* 60: 85-98.

Posthumus, H., Morris, J., Hess, T. M., Neville, D., Phillips, E., & Baylis, A. (2009). Impacts of the summer 2007 floods on agriculture in England. *Journal of Flood Risk Management,* 2(3), 182-189.

Risbey, J., Kandlikar, M., Dowlatabadi, H., & Graetz, D. (1999). Scale, Context, and Decision Making in Agricultural Adaptation to Climate Variability and Change. *Mitigation and Adaptation Strategies for Global Change,* 4, 137-165.

Robertson, R., Nelson, G., Thomas, T., & Rosegrant, M. (2013). Incorporating Process-Based Crop Simulation Models into Global Economic Analyses. *American Journal of Agricultural Economics*, 95(2), 228-235.

Robison, L. J., & Barry, P. J. (1987). *The competitive firm's response to risk*. New York: Macmillan.

Shafran, A.P. (2011). Self-protection against repeated low probability risks. *Journal of Risk and Uncertainty*, *42*(3), 263-285.

Schlenker, W., Hanemann, W.M. & Fisher, A.C. (2005). Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach. *American Economic Review,* 95(1), 395-406.

Serra, T., Goodwin, B. K., & Featherstone, A. M. (2005). Agricultural Policy Reform and Off- farm Labour Decisions. *Journal of Agricultural Economics,* 56(2), 271-285.

Simmons, P. (2002). Why do farmers have so little interest in futures markets? *Agricultural Economics,* 27(1), 1-6.

Slovic, P. (1987). Perception of Risk. *Science,* 236, 280-290.

Smit, B., McNabb, D., Smithers, J. (1996). Agricultural adaptation to climatic variation. *Climatic Change,* 33, 7–29.

Smit, B., Blain, R. & Keddie, P. (1997). Corn hybrid selection and climatic variability: Gambling with nature? *The Canadian Geographer,* 41, 429–438.

Smit, B., & Skinner, M. (2002). Adaptation options in agriculture to climate change: a typology. *Mitigation and Adaptation Strategies for Global Change,* 7, 85–114.

Smith, V.H., & Goodwin, B.K. (1996). Crop insurance, moral hazard, and agricultural chemical use. *American Journal of Agricultural Economics,* 78, 428–438.

Smithers, J., & Smit, B. (1997). Human adaptation to climatic variability and change", *Global Environmental Change,* 7 (3), 129–146.

Tack, J., Harri, A., & Coble, K. (2012). More than mean effects: modeling the effect of climate on the higher order moments of crop yields. *American Journal of Agricultural Economics,* 94, 1037-1054.

Tobin, G. A. & Montz, B. E. (1997). *Natural Hazards: Explanation and Integration.* New York: Guildford Press.

Tversky, A., Kahneman D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science,* 185, 1124-1131.

Velandia, M., Rejesis, R.M., Knight, T.O., & Sherrick, B.J. (2009). Factors Affecting Farmers' Utilization of Agricultural Risk Management Tools: The Case of Crop Insurance, Forward Contracting, and Spreading Sales. *Journal of Agricultural and Applied Economics,* 4, 107-123.

Wheater, H. (2006). Flood hazard and management: A UK perspective. *Philosophical Transactions of the Royal Society A,* 364(1845), 2135–2145.

Woldehanna, T., Lansink, A. O., & Peerlings, J. (2000). Off-farm work decisions on Dutch cash crop farms and the 1992 and Agenda 2000 CAP reforms. *Agricultural Economics,* 22(2), 163-171.

Zilberman, D., Zhao, J., & Heiman, A. (2012). Adoption Versus Adaptation, with Emphasis on Climate Change. *Annual Review of Resource Economics*, 4(1), 27-53.