Natural Disasters and Agriculture:

Individual Risk Preferences towards Flooding

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Abstract

This study contributes to the understanding of behavioural responses to climate change induced extreme weather events. It suggest a microeconometric method for measuring flooding related risk preferences of affected individuals. The method is outlined using the empirical case of agricultural production in floodplains of the UK over 28 years. A quasi-experimental approach to measure differences in the risk attitudes of farmers located in high flooding risk areas versus farmers located in low flooding risk areas is followed. Changes in flooding risk related behaviour over time is analysed and marginal effects of different individual and disaster related characteristics for this behaviour are investigated. Beside a moments based risk estimation approach the study also applies a dynamic panel estimator. The estimates suggest that the average farmer located in a high flooding risk area is prepared to pay about 6% more of his profit for insuring against the higher risk of flooding compared to farmers in low flooding risk areas. The significance of considering individual risk preferences for an efficient flood policy design is discussed using the example of voluntary agreements for the maintainance of flood defences.

Keywords

Extreme Events, Risk, Agriculture, Natural Experiments, Behavioural Adaptation

1 - Introduction

There is a need to refine our understanding of how individuals respond to risk and uncertainty caused by rare events related to climate change (Chavas et al 10). Whereas the economic implications are widely investigated at a sectoral and macroeconomic scale (see e.g. Deschenes and Greenstone 07 or Jonkman 08), the implications for individual decision making are widely neglected. This holds also with respect to agricultural producers. However, the design of effective adaptation measures crucially depends on the knowledge about the driving factors for changes in individual risk attitudes and adaptation patterns. Kenyon et al (2008) report that one major reason for a low uptake of such climate change related adaptation measures are the economic agents' attitudes or preferences towards risk and uncertainty related to extreme weather events.

Flooding is a primary example for such climate change related rare events in all parts of the world: At the time writing this paper Sri-Lanka faces the worst floods in the conutry's recent history destroying homes, schools and agricultural land (Guardian, 20/01/2011). The states Queensland and Victoria in Australia are hit by devastating floods where about a quarter of the state of Queensland has been affected by the floods (BBC, 20/01/2011). In August 2010 severe storms and flooding hit the region Saxony in eastern Germany. The 2010 Central European floods were a devastating series of weather events which occurred across several countries during May, June and August with at least thirty-seven people died in the floods and approximately 23,000 people evacuated. France experienced the 2010 Var floods as a result of heavy rainfall in the southern parts of the country in June. The Cornwall floods in the UK in November 2010 led to the evacuation of more than 100 homes. The damage for agricultural production caused by such flooding consists of lost yields and crop damage, loss of grass for animal feed, damages to farm buildings, machinery and other assets.

Extreme events such as flooding are one of the main channels through which climate and socioeconomic systems interact. Such events can be considered as changes or spatial variation in rules governing individual behaviour which are assumed to strictly satisfy the randomness criterion with respect to empirical modelling of such behaviour. Hence, by making use of these "natural experiments" the analyst might be able to identify marginal changes in individual behaviour due to these events by effectively and credibly controlling for unobserved characteristics (e.g. locational attributes and events or individual behavioural differences).

This study empirically investigates the following questions: How do the risk preferences of farmers in areas with high flooding risk differ from those located in areas with low flooding risk? How do these risk preferences change over time? What is the marginal effect of different input levels on the individual risk preferences and how does this effect differ between high and low flooding risk areas? What is the marginal effect of different flood events on risk preferences over time? Finally, policy conclusions are drawn towards a more effective flood risk policy design. The paper is organised as follows: Section 2 outlines the research problem to be investigated and gives a brief review of relevant literature. Section 3 describes the research set-up whereas section 4 introduces the conceptual model. Section 5 outlines the econometric implementation as well as the datasets used and is followed by section 6 which reports and discusses the results. Finally section 7 concludes.

2 - Problem and Literature

The frequency of heavy precipitation events has increased for most regions in the world and is considered to continue in the future. There is evidence of increasing floods in all continents and states with a high certainty that the risk of flooding will increase further in the future (UNESCO 09, IPCC 07). 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 04, Posthumus et al 09). Based on survey data and derived cost estimates Posthumus et al (09) report total costs of about 1% of the gross value added for the agricultural industry in England due to the floodings 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 labour. 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 the scientific and "real" evidence, policymakers are becoming increasingly concerned about flooding and flood risk management. Tobin and Montz (97) have impressively outlined the tied relationship between flood disasters and the demand by the public for a policy response. Parker (00) 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 (05) identify three key phases of incremental flood policy change since World War II: land drainage, flood defence 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 defences, flood warning systems, public awareness raising, landuse 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.

Johnson et al (05) point out that there is, however, no guarantee that the nature of the policy issues raised by a major flood disaster will offer anything more than post-event response and recovery. Mileti (99) emphasises that historically, flood management has been the domain of meteorologists, hydrologists, planners and engineers, with the preferred flood management options being engineered structural solutions, such as dams and embankments. Others argue that although this traditional approach may meet short-term goals, in the long term it has failed to reduce the economic loss from flooding and as flooding increases it is impractical, expensive and unsustainable. Effective flood prevention policy, though, has to move beyond the linear hazard-dose-response relationship often associated with natural disasters (Smith et al 06). Kenyon et al (08) suggests to link flood risk management, agriculture and land use management via payments to farmers and land managers delivered as an integral part of the EU's Common Agricultural Policy.

The consideration of individual flood risk perceptions and their development over time are crucial for a higher effectiveness of flood management in the future. Different individuals (house owners, landowners, farmers etc.) experience varying degrees of risk associated with flooding, i.e. their "perception" of such risk differs due to known and unknown factors leading to different preferences towards the risk of flooding. Beside the frequency, magnitude and proximity of the flooding event also the individual ability to manage and adapt to the flooding event as well as local and regional defence measures play a role here (Priest et al. 05). Furthermore, the individual's general attitude towards risk and uncertainty. Risk preferences can be assessed by qualitative and quantitative means and there are various models to explain the relationship between natural hazard, individual vulnerability and exposure, and the resultant individual risk (e.g. Couture et al 2010).

The main assumption of these (static) models is that individual risk encompasses a combination of hazard, exposure and vulnerability (e.g. representing the sides of the “risk triangle”) implying that if any one element increases/decreases the risk changes accordingly. Hence, given an increase in climate change related flooding hazard for the UK, spatially differing quantity and quality of flood and drainage systems as well as changes in regional land uses and urbanisation have amplified the risk of the physical flood hazard for the individual agricultural producer over time. The individual’s preferences towards the risk of flooding is based on the perception of these interlinked factors and the dynamics involved and also reflects the general risk attutides of the individual. Carbone (06) points out that individuals adjust to the risks presented by natural disasters in a number of ways: move out of the harmful area, self-protection, or insurance. However, for an agricultural land owner the first option seems not a realistic option of effective flood risk management due to the costs implied as well as the restrictions on land availability etc.

The economic evaluation of flood risk management policy with respect to agricultural production has to consider the individual farmers’ risk preferences. The different instruments of current UK flood policy aim to influence agricultural producer decisions via changes in relative input and output choices. Hence, the assumptions made by policy makers regarding the production structure and farmers’ responses to restrictions and/or payments in a risk averse environment are crucial for the anticipated flood policy outcome. The specific policy design should be a function, not only of the climatic and hydrogeological conditions that prevail in the region and farmers’ production technology but also their risk preferences. These preferences define the way the farmers use inputs to hedge against production risk due to natural disasters (see Groom et al 08). A more effective management of flood risks will only be achieved by considering differences in individual risk preferences towards flooding based on quantitative measures. The following empirical research aims to shed light on the preferences of individual farmers towards flood risk as well as the development of such preferences over time. The results should provide crucial insights for policy makers with respect to a more cost-effective design of future flood risk management policies.

There is a comprehensive literature on all aspects of flooding. The following overview considers those constributions directly related to risk and agricultural production: Deschenes and Greenstone (07) evaluate the economic impacts of random weather fluctuations on agriculture by estimating the effect of random year-to-year variation in temperature and precipitation on agricultural profits. Goodwin (08) discusses the implications of climate variability for agricultural production and risk management whereas Banerjee (07) estimates the effect of floods on the wages for agricultural labor in a developing context. The latter concludes that floods have generally positive implications for wages in the long run if favorable market conditions are in place, however, a declining effect on wages in flooded areas. The magnitude of flood impact depends on the relative flood proneness of a district and the relative severity of flood conditions. Smith et al (06) focuses adjustment behaviour of natural disaster affected households and businesses by using the example of different hurricanes. They find that the economic capacity of the household to adjust explains most of the variance in demographic groups’ patterns of adjustment to the disaster damage. Kunreuther et al (85) proposes a model of adoption of protective activities which emphasizes the importance of interpersonal communication and past disaster experience. At a regional level Kenyon (07) evaluates different flood risk management options for Scotland based on a participatory approach and concludes on the relative preferability of individual options. In a subsequent study Kenyon et al (08) found that while there are currently few institutional links between flood risk management and agriculture, there is great potential for agriculture to become part of the solution. The authors conclude that policy needs to be ‘‘flood proofed’’ so that perverse incentives are avoided. Further, they find that the provision of accessible and effective advice and education is crucial and suggest that agricultural policy also needs to offer a package of measures to address flood risk and to address flood risk also at single farm level. Finally, Browne and Hoyt (00) investigate empirical evidence on the demand for flood insurance and conclude on income and price as the key determinants for one’s decision to purchase flood insurance. Flood insurance purchases at the state level are found to be highly correlated with the level of flood losses in the state during the prior year.

Several authors, hence, acknowledge the need for considering the heterogenity among individual preferences towards the risk of flooding with respect to an effective flood policy design. Furthermore, the dynamic nature of such preferences and the potential lag in the individual behavioural response to flooding events and policy measures is emphasised. However, so far, no contribution exists that tackles the empirical measurement of such flood risk preferences at the level of the individual economic agent.

3 - Research Set-Up

The main research hypothesis is: Farmers' preferences towards the risk of flooding are heterogenous. The heterogeneity in flood risk preferences is caused by spatial, temporal and individual characteristics of which some are observable, others are, however, unobservable. Knowledge about these individual preferences and causal factors for their heterogeneity and development over time is crucial for effective flood policy design. Hence, the subsequent empirical analysis aims to deliver the following: (1) The measurement of flood risk preferences of farmers located in areas with differing degrees of flooding risk and changes in these preferences over time. (2) The measurement of the link between input levels and flood risk preferences. (3) The determination of the marginal effect of different flood events on those risk preferences. (4) A scenario analysis with respect to farmers' input choices using different assumptions regarding the individual farmers' flood risk preferences.

Rosenzweig and Wolpin (00) point to the difficulties of carrying out experiments with near-perfect random treatments to answer questions of general importance and the lack of credibility of many of the assumptions of standard instrumental variable studies. Hence, economists have sought out "natural experiments", random treatments that have arisen serendipitously. These putative natural experiments are usually changes or spatial variation in rules governing individual behaviour which are assumed to strictly satisfy the randomness criterion. The advantage of the natural natural experimental approach is that the assumption of randomness for the instrumental variables employed is more credible than for instruments used in other studies. Carbone (06) points to the advantages of using natural experiments to control for other unobserved characteristics (i.e. locational attributes and events) with respect to spatially delineated risks (see also Greenstone and Gayner 09). The study by Couture et al (10) indicates that risk preferences measured through stated and revealed preference approaches are consistent.

Based on the natural natural experimental approach we choose the following research set-up: We build two samples of farms differing in their exposure to the risk of flooding as defined by relevant policy agencies and based on observed past flooding events' probabilities (see Environment Agency 09). To control for production technology related differences among the farms we focus only on cereal and general cropping type farms. Self-selection of more risk-averse farmers into the low flooding risk sample can be assumed as negligable as the relocation of the farm is not a realistic option. Socioeconomic characteristics with respect to farmers and farm households can be assumed to be randomly distributed over both samples. Given the EU commodity market regimes in place for all major crops, price and market related risk and uncertainty can be assumed to be the same for the farms in both samples, consequently no systematic selection bias should be present. We employ longitudinal data for our two samples to be able to consider lagged behavioural responses with respect to disasters and policy. Overall, no systematic selection bias should be present in our samples and we are able to investigate generalities in behavioural responses across different flooding crises. Hence, our quasi-experimental research approach follows not a traditional natural experiment set-up including a treatment and control group, rather uses a sequence of natural treatments for the same group of individuals compared to a 'benchmark' group of individuals without any such treatment (i.e. control sample).

4 - Conceptual Model

Our basic assumption is that the source of risk related to crop production is predominantly climatic: Given the current framework of the Common Agricultural Policy (CAP) we assume that output prices and input prices are nonrandom, hence, the risk related to climate change, and here predominantly related to floods and droughts, is the only significant source of production risk (see also Antle 83, Kim and Chavas 03, Groom et al 08).[1]

Risk Attitudes

Let p denote the output price for a single crop, $f(\cdot)$ is a continuous and twice differentiable production function, $\mathbf{X}$ is the K vector of inputs and $\mathbf{r}$ as the corresponding vector of unit input prices. Climate risk including the probability of natural disasters like flooding affects crop yield through the variable ε with the distribution $g(\cdot)$ which is not affected by the individual farmer's decisions. A risk averse farmer maximizes expected utility of profit

[1] Different contributions point out that this assumption is not critical for the analysis as European farmers can be generally assumed to be price-takers. Allowing also for price risk would not yield significant changes in the analysis.

(1) $\max_{\mathbf{X}} E[U(\pi)] = \max_{\mathbf{X}} \int [U(pf(\varepsilon,\mathbf{X}) - \mathbf{r}'\mathbf{X})] dg(\varepsilon)$

where $U(\cdot)$ is the Von Neumann-Morgenstern utility function. The optimal solution for input vector element X_k depends on (p, **r**) as well as the shape of the functions $U(\cdot), f(\cdot)$ and $g(\cdot)$. Hence, the first-order condition for input X_k is

(2) $E[r_k \times U'] = E\left[p\frac{\partial f(\varepsilon,\mathbf{X})}{\partial X_k} \times \frac{\partial U(\pi)}{\partial \pi}\right] = E\left(\frac{\partial f(\varepsilon,\mathbf{X})}{\partial X_k}\right) + \frac{cov(U',\partial f(\varepsilon,\mathbf{X})\partial X_k)}{E(U')}$

and the shape of the utility function determining the individual risk aversion. For a risk averse farmer the second term on the right-hand side of (2) differs from zero measuring the deviation from the risk neutral case. If the use of input k is risk increasing, the marginal risk premium increases with X_k and consequently the desired level of X_k decreases, ceteris paribus. Hence, solving (2) for X_k yields the equilibrium input quantity in terms of *p* and **r**. However, the chosen technology specification and the distribution of ε needs to be known as well as the individual farmer's risk preferences.

By following a flexible estimation approach (see e.g. Antle 87) we are able to estimate the solution to the farmer's optimisation problem solely as a function of input levels. Maximizing the expected utility of crop profit with respect to any input equals the maximization of an unspecified function $h(\cdot)$ of moments for the distribution of ε which are functions of **X** (see also Groom et al 08)

(3) $\max_x E[U(\pi)] = h[\mu_1(\mathbf{X}), \mu_2(\mathbf{X}), \dots, \mu_m(\mathbf{X})]$

with $\mu_j = E(\Pi - \mu_1)^j, j = 2, \dots, m$ denotes the *m*-th moment of farmer i's profit. To estimate the risk attitude related parameters for a population of farmers we apply a moments based approach introduced by Antle (83 and 87) and making use of (3). This approach is based on the assumption that all farmers produce with similar technology which e.g. can be described by the related profit distribution. The first order condition for the *k*-th input based on (3) is given by

(4) $\frac{\partial \mu_1(\mathbf{X})}{\partial X_k} = \varphi_{1k} + \varphi_{2k}\frac{\partial \mu_2(\mathbf{X})}{\partial X_k} + \varphi_{3k}\frac{\partial \mu_3(\mathbf{X})}{\partial X_k} + \varphi_{4k}\frac{\partial \mu_4(\mathbf{X})}{\partial X_k} + \dots + \varphi_{mk}\frac{\partial \mu_m(\mathbf{X})}{\partial X_k}$ with

(5) $\varphi_{jk} = \frac{-1}{j}! \times \left(\frac{\partial F(\mathbf{X})}{\partial \mu_j(\mathbf{X})} / \frac{\partial F(\mathbf{X})}{\partial \mu_1(\mathbf{X})}\right)$

and so, φ_{jk} represents the average population risk attitude parameter relating to the *j*-th moment ($j = 2, \dots, m$) and the *k*-th input's first order condition, i.e. m unknown parameters for each input. Hence, the marginal contribution of input k to the expected profit $(\partial \mu_1(\mathbf{X})/\partial X_k)$ is conceptualized as a linear combination of the marginal contributions of input k with respect to the other moments, i.e. for the variance: $(\partial \mu_2(\mathbf{X})/\partial X_k)$, for the skewness: $(\partial \mu_3(\mathbf{X})/\partial X_k)$, and for the kurtosis $(\partial \mu_4(\mathbf{X})/\partial X_k)$ etc.

Risk Aversion

Following Pratt (64) and Menezes et al (80) the parameters φ_{2k} and φ_{3k} can be interpreted as measuring Arrow-Pratt absolute risk aversion (*ap*) and downside risk aversion (*ds*), respectively:

(6) $ap = -\frac{\partial F(\mathbf{X})/\partial \mu_2(\mathbf{X})}{\partial F(\mathbf{X})/\partial \mu_1(\mathbf{X})} = 2\varphi_2$ (7) $ds = \frac{\partial F(\mathbf{X})/\partial \mu_3(\mathbf{X})}{\partial F(\mathbf{X})/\partial \mu_1(\mathbf{X})} = -6\varphi_3$

If $ap > 0$, this implies that the average farmer in the population is risk-averse. If $ds > 0$, this implies that the average farmer in the population is averse to downside risk. These measures can be estimated for each input to obtain input specific measures of risk aversion (Antle 87).[2]

The latter coefficient is of particular interest with respect to the analysis of the effects of natural disasters on producer decisions and risk attitudes. Downside risk is related to skewed (asymmetric) statistical profit distributions occuring in the case of aversion to disastrous events. Hence, downside risk aversion can be interpreted as a preference for disaster avoidance (see e.g. Menezes et al 80). Using equation (7) such downside risk can be measured for a population of farmers defined over space and time. E.g. measuring ds for a population of farmers located in areas with a high flooding risk hf and for a population of farmers located in areas with a relatively low flooding risk lf (by controlling for soil quality characteristics and other space and time related differences) can give insights into the particular preferences towards flooding avoidance. It can be expected that the average farmer located in high flooding risk areas should show a significantly higher downside risk aversion than the average farmer located in low flooding risk areas:

(8) $ds_{hf} > ds_{lf}$

Finally, if panel data is available changes in ds for populations of farmers located in areas with differing flooding risk can be traced over time.

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[2] In this case $\theta_{jk} = \theta_j$, $ap_k = ap$ and $ds_k = ds$. See Groom et al (08) for a differing view.

The magnitude and range of risk attitudes in a population of farmers can be interpreted in terms of the risk premium implied by the estimates for *ap* and *ds*. Following Newbery and Stiglitz (81) and Antle (87) and assuming that the individual farmer is concerned only by the first three distributional moments as defined above, the risk premium ρ as a proportion of expected profit (i.e. the relative risk premium), is approximated by

(9) $$\frac{\rho}{\mu_1} = \mu_2 \frac{ap}{2\mu_1} - \mu_3 \frac{ds}{6\mu_1}$$

and can be also estimated for each input to obtain input specific measures of the relative risk premium. Note, that $\frac{\rho}{\mu_1}$ varies at individual farmer's level, hence, relative risk premia can be measured for each farmer in the sample, for the average farmer in a population as well as at different points in time. rp > 0 means, that the individual farmer is characterized by a positive willingness-to-pay to be insured against climate-change related risk including disastrous events like flooding.

Risk Adaptation

Risk attitudes vary across farmers and time, hence, the estimated risk premium can be expected to vary over farmers and time. As farmers adapt to the risk implied by a higher probability of natural disasters like flooding as a consequence of climate change, the risk premium *rp* changes according to the adaptation pattern chosen. Hence, variation in *rp* over space and time can be also interpreted as a measure for differences in chosen adjustment decisions on farm level.

Smith et al (06) point to the importance of the economic capacity of households with respect to explaining differences in adjustment patterns related to natural disasters. Messner and Meyer (05) indicate that the level of information with respect to likely damage and vulnerability is crucial for changing persistent behavioural patterns of disaster risk adaptation. Hence, individual learning plays a role in explaining such behavioural changes over time (see also Reilly and Schimmelpfennig 00, Meza and Silva 09). Panel data would be needed to be able to adequately model such patterns and to empirically disentangle significant factors for changes in such patterns. Induced innovation and technological change based on the adoption of agricultural adaptation measures as e.g. the building of effective dams, the opening of new lands or training and crop development activities take time (see e.g. Plusquellec 90). Reilly and Schimmelpfenning (00) conclude that irreversibilities with respect to agricultural capital infrastructure are important to consider: certain capital assets might have to be replaced by time-consuming processes, hence, significant adjustment costs are unavoidable. Different contributions investigate the hypothesis that natural disasters might have positive economic consequences for affected areas, i.e. a positive productivity effect via an accelerated replacement of capital using most recent production technologies (e.g. Albala-Bertrand 93, Okuyama 03, Hallegatte and Dumas 09). Kenyon et al (08) conclude that the low uptake of wetland management options as part of voluntary management agreement type environmental schemes is predominantly due to a lack of advice, low payment rates, and prevailing attitudes among farmers.

To empirically analyze the drivers for differences in risk adaptation behaviour on individual farm level the risk premium approximated by equation (9) can be described as a function of different factors:

(10) $$\rho_{it} = \frac{1}{2}\mu_{2it} ap - \frac{1}{6}\mu_{3it} ds = f_{it}(\rho_{it-n}, \boldsymbol{\gamma}, \boldsymbol{\tau}, \boldsymbol{\omega}, \mathbf{d})$$

where $\boldsymbol{\gamma}$ denotes a vector of information and human capital related variables (as e.g. level of education, age, learning-by-doing, but also policy actions like wetland management campaigns or improved flood information systems), $\boldsymbol{\tau}$ as a vector of social interaction and spillover related variables (as e.g. the intensity of social networks, distance to neighboring farms also affected by the natural disaster), $\boldsymbol{\omega}$ as a vector covering the effects by production related behaviour (as e.g. land use practises, size of operation, rate of technical change, irreversibilities, investments), and $\mathbf{d}$ relates to a vector of variables indicating the occurence of particular flooding events. The persistence of behavioural patterns with respect to the (non-)adaptation to a climate change induced increase in flooding risk can be modelled by the incorporation of lagged variables. Lagged variables reflect the assumed correlation of risk attitudes (as measured by ρ_{it}) at time t with risk attitudes at time t-n (ρ_{it-n}). Finally, some of these variables are endogenously determined by the specific production and environmental conditions prevailing at farm i.

Risk Preference Scenarios

The economic evaluation of flood risk management policy has to consider the importance of estimating the farmers' risk preferences. Current flood policy in the UK includes the following elements: flood defences (e.g. managed river channels, walls and raised embankments, flood barriers and pumps), locating property outside the floodplain (siting new buildings in areas of lowest risk), flood warning services as well as private insurances. The different flood policy instruments aim to influence producer decisions via changes in relative input and output choices. Hence, the assumptions made by policy makers regarding the production structure and farmers' responses to restrictions and/or payments in a risk averse environment are crucial for the anticipated flood policy outcome. The specific policy design should be a function, not only of the climatic and hydrogeological conditions that prevail in the region and farmers' production technology but also their risk preferences. These preferences define the way the farmers use inputs to hedge against production risk (see Groom et al 2008).

We consider three different scenarios which differ only with respect to the availability of information about farmers' risk preferences for the policy maker: (a) farmers are risk neutral and simply attempt to maximize profit; (b) farmers have preferences over the variance of profit; (c) farmers have preferences over both the variance and skewness of profit. Based on these scenarios the policy effect is evaluated using the input mix, the moments of profit and the estimated average risk premia (see equations 6 and 7). Hence, the impact on farmers located in high risk flooding areas is estimated by using the elasticities between all inputs K based on the system of first order conditions for expected profit maximization given in equation (4). Applying the implicit function theorem and using the obtained parameter estimates from above we estimate

$$(11) \quad \frac{dK}{dK_{-1}} = \frac{\partial^2\mu_1/\partial K\partial K_{-1} - (ap_K/2)\partial^2\mu_2/\partial K\partial K_{-1} + (ds_K/6)\partial^2\mu_3/\partial K\partial K_{-1}}{\partial^2\mu_1/\partial K^2 - (ap_K/2)\partial^2\mu_2/\partial K^2 + (ds_K/6)\partial^2\mu_3/\partial K^2}$$

for each pair of inputs, where K = capital, labor, intermediates, and chemicals, and ap_K and ds_K refer to the measured Arrow-Pratt absolute risk aversion and downside risk aversion parameters, respectively (see also Kumbhakar 2007). For scenario (a), equation (11) is evaluated assuming risk neutrality, i.e. ap = ds = 0. Scenario (b) assumes that there is no down-side risk aversion, i.e. ds = 0, whereas scenario (c) considers full risk preferences using the previously estimated risk parameters. Equation (11) implies that for each farm and year elasticities are assessed after the use of these inputs have actually responded.

5 - Data and Econometrics

Our empirical case are floodings in the UK for the period 1980 to 2008 covering 28 years. Based on individual farm survey data from the UK Farm Business Survey (Farm Robust Type 1 'cereals' and 2 'general cropping'), a high flooding risk sample (sample 1) and a low flooding risk sample (sample 2) are created following the policy relevant Flood Risk Mapping exercise conducted by the Environment Agency in 2009 (see Environment Agency 2009). Following this mapping each holding can be located based on the percentage of its area within the floodplain. Hence, sample selection takes place along naturally defined flood risk zones including all regions in the UK. We augment this production and socioeconomic data by soil quality, temperature and precipitation related information based on datasets made available by the UK Met Office. Further, individual flood event related data is used based on statistics released by the Dartmouth Flood Observatory. Sample 1 (i.e. treatment sample) includes farms with more than 20% of their agricultural area located within the floodplain, sample 2 (i.e. control or benchmark sample) includes farms with less than 20% of their agricultural area located within the floodplain. Using simple hypotheses testing procedures different alternative percentage thresholds have been tested (summary statistics are not reported here due to space limitations).

Based on the conceptual framework outlined above and using these two samples we employ the following estimation procedure: (i) In a first step, we estimate the conditional expectation of profit using a second-order flexible quadratic functional form estimated in a random effects specification (see e.g. Greene 03) and controlling for environmental and locational characteristics of the farms.[3] The residuals of this regression are used to compute the conditional higher moments following equation (3) outlined above. Hence, unlike earlier studies (e.g. Groom et al 2008) we consider the link between risk preferences and environmental and locational conditions already at this stage of estimation which leads to a more efficient estimation avoiding the need for instrumental regression techniques later on. (ii) These conditional higher moments are then regressed on all input levels, squared and cross-products (following the quadratic specification) as well as control variables using again a random effects estimator. Further, analytical expressions for marginal effects and elasticities with respect to all inputs are then estimated using the delta method.[4] (iii) In a third step, we apply a seemingly unrelated regression estimator (SURE)

[3] We use the variables on a per ha bases and rescale them by their standard deviation to increase the model fit.

[4] The delta method evaluates the marginal effects and elasticities at one point that represents the average value of the elasticity for a particular set of observations, allowing standard errors to be computed for inference even though the elasticity computation involves a combination of econometric estimates and data (e.g. Oehlert 92).

in a random effects specification for unbalanced panel data (see Biorn 04) to estimate the system of input equations outlined by equation (4) for the inputs capital, labor, intermediates and chemicals. We also compute the bootstrapped biased-corrected standard errors for these estimates to ensure sufficient statistical significance (see Horowitz 01). Using the estimates obtained from the system estimation we then compute the sample average Arrow-Pratt absolute risk aversion measure (*ap*) and the downside risk aversion measure (*ds*) for each input following equations (6) and (7). Further, we estimate the relative risk premium ρ (equation 9) for each input at sample average and for each observation.

These different estimation steps are undertaken for both samples, the treatment and control (or benchmark) sample. (iv) Using these different measures for risk preferences towards flooding we then conduct several hypotheses tests to elicit significant differences between the the two samples based on relevant hypotheses regarding risk neutrality, downside risk aversion and equality of risk preferences across samples. Furthermore, considering only the high flood risk sample (treatment sample) and following equation (10), we (v) estimate the marginal effects of potential factors for differences in risk premia at farm level and changes over time by applying a dynamic panel data estimator (DPD) in a linear GMM-type specification (as introduced by Arellano and Bover 95 or Blundell and Bond 98). We include lags of the dependent variable (relative risk premium) as regressors to account for potential lags in flood risk adaptation behaviour as well as valid instruments to account for potential endogeneity with respect to some of the regressors. Again, we also compute the bootstrapped bias-corrected standard errors for these estimates and test for the quality of the chosen instruments by using appropriate test formulas (see e.g. Bowsher 02). Finally, (vi) based on equation (11) outlined above and using the obtained parameter estimates from estimation step (iii), we estimate input elasticities at the treatment sample means applying the delta method and assuming different flood policy relevant scenarios as discussed above.

This research contributes to the literature in the following ways: To the author's knowledge this is the first study aiming to empirically measure individual risk preferences towards the risk of flooding. We use a quasi-experimental research set-up based on a naturally occuring sequence of flooding disasters over more than 25 years. Hence, unlike previous empirical studies on natural disasters we use a comprehensive panel data set as well as a more efficient estimation procedure. Finally, we try to disentangle the effects of policy measures on individual behaviour towards extreme natural events.

6 - Results

All estimated models show a satisfactory overall significance (model quality estimates are not shown here due to space limitations). The proportion of the total variance contributed by the panel-level variance (parameter rho) shows for all random effects models a significant level. The Sargan test of overidentification confirms the validity of the instruments chosen for the GMM dynamic panel estimation. The linear hypotheses tests on the joint significance of groups of parameters indicate that the inclusion of lagged values for the risk premium, the flooding events, the flooding characteristics, the policy changes, and farm and farmer characteristics leads to a higher estimation accuracy and estimates' robustness.

Risk Parameters and Premia

The estimates for the risk related parameters show significantly positive values for the farms located in high flooding risk areas and mainly negative values for the farms located in low flooding risk areas (see table 1). These findings imply positive Arrow-Pratt and downside risk aversion parameters for farmers in the floodplain suggesting that on average cereal and general cropping type farms located in high flood risk areas have preferences over higher order moments of profit since they are averse to risk (profit variance) and downside risk (profit skewness). On the other hand, the estimates for farmers located in low flood risk areas imply no significant preferences over higher order of profit. The input-specific estimates reveal high values with respect to capital and intermediates suggesting that those inputs are most affected by flooding related risk. These estimates further suggest that the average farmer located in a high flood risk area is prepared to pay about 8% of his profit for insuring against the higher risk of flooding. This is indicated by the overall relative risk premium for the sample period of 28 years.

(Table 1 about here)

Recalling that the system of equations outlined in equation (4) is derived from the first order conditions for expected profit maximization, economic theory suggests that the constant parameter (reflecting the origin of the estimated function) should be equal to zero for each input (see Antle 87). If these parameters significantly deviate from zero this could be interpreted as inefficiency with respect to the use of the specific input, hence, a deviation from profit maximizing behaviour. The estimates shown in table 1 for the individual input constants suggest that farmers located in low flooding risk areas use inputs more efficiently than farmers located in high flooding risk areas. Given the marginal cost, capital, labor and intermediates (i.e. energy, seeds, water, etc.) are not used efficiently by farmers with a significant share of their agricultural area in the floodplain. We observe significant positive estimates for these constant terms implying that these inputs have been overused by those crop producers during the period investigated.

The estimates for the marginal effects of the moments of the profit distribution with respect to all inputs and time reveal the following (see table 3): Capital and intermediates have a positive and significant impact upon expected profit for both farms in high and farms in low flood risk areas. Chemicals show a negative effect on expected profit whereas time has a significant positive effect on expected profit for both samples. Labor, however, shows a significant positive effect on expected profit for farms in the high flood risk sample but a significant negative effect on expected profit for the control sample. This suggests that labor is a crucial input with respect to risk stemming from natural disasters like flooding and is consistent with earlier empirical studies (Groom et al 08, Antle 87) concluding that more labor reduces risk and hence expected profit because crop plant growth problems can be monitored more effectively. The extensive use of chemicals on the other hand leads to declining expected profit and an increase in crop production risk. These findings for labor and chemicals are in line with the marginal effects regarding the variance of profit where both inputs show a significant risk decreasing effect for the high flood risk sample. Over time the expected profit of crop production increases, however, also the variance around the mean expected profit, hence, the risk of production, increases significantly for both samples. Finally, labor and intermediates have a significant effect on profit skewness: Whereas the use of labor marginally decreases the downside risk related to extreme events, the use of intermediates marginally increases such downside risk. Hence, labor intensive (and probably a more extensive) production leads to a significantly lower risk exposure for crop farms. This effect was found to be more than 10 times higher for farms in high flood risk areas (see table 3).

The extent of risk aversion appears to differ for farmers located in high flood risk areas and those located in low flood risk areas. We test the hypothesis of equal risk preferences across the two samples by applying a Kolmogorov-Smirnov test statistic. The test values clearly reject this hypothesis for all inputs and suggest a significant difference in the risk preferences of the farmers in the two samples related to natural disasters. Hence, we can conclude that farmers in high flood risk areas are willing to give up more of their expected profit in order to receive future profit with a higher certainty. Further, those farmers are prepared to pay relatively more to hedge against such disastrous events (see also Groom et al. 08). Self-selection of more risk averse farmers into the sample of high flood risk farmers and/or of less risk averse farmers into the sample of low flood risk farmers can be neglected due to the high costs of relocating entire farm holdings. Furthermore, the chi square test statistics strongly reject the hypothesis of "risk neutrality (AP=DS=0)" as well as the hypothesis of "no downside risk (DS=0)" for both samples and all inputs.

Risk Premia Dynamics and Adaptation

The trends of the risk premia for the two samples diverge especially from 2003 on: whereas the risk premium shows a steady increase for the high flood risk sample, it has been decreasing with high volatility for the low flood risk sample. Hence, the estimated variation in the relative risk premia over space and time indicates significant differences in flood risk adjustment behaviour at farm level. The dynamic estimation of factors for the distribution of the risk premium over time revealed the following for farmers located in high flood risk areas (see table 2):

(Tables 2 and 3 about here)

(i) *Previous Disaster Preferences*: The significant positive coefficients for the lagged risk premia (two years) suggest that risk adaptation behaviour is indeed influenced by past behaviour. Time intensive individual learning with respect to effective and efficient flood risk mitigation measures might play a role here (Meza and Silva 09). Also, prevailing attitudes towards the responsibility for flood risk mitigation measures (individual, local, state etc.) or simply the process of getting used to the need for flood adaptation strategies (Kenyon et al 08). The concept of 'path dependence' could be used to explain some of this significance, i.e. how the risk preferences towards extreme natural events like flooding are limited/predetermined by the adaptation measures made in the past, even though the past flood risk exposure may no longer be relevant (e.g. Bernheim 94 or Page 06).

(ii) *Individual Flood Events and Characteristics*: Single flooding events were found to affect the relative risk premium at individual level over time. A significant positive coefficient was found for the following flood events: 10/1990 (Southern England), 9/1992 (Midlands, East Anglia), 12/1999 (South East), 11/2000 (South East), 1/2003 (Southern England), 6/2007 (Yorkshire), 7/2007 (Oxfordshire), and 1/2008 (Yorkshire). The estimates reveal that after a signficant effect of the floods in 1990 and 1992 the effect of individual events somewhat decreased before increasing again in most recent years (2007 and 2008). The estimates further suggest that the longer the total flooding time per year and the more farms are affected per year in a given area, the stronger are the individual preferences towards the risk of flooding. However, the overall severity of the flooding event (based on the Dartmouth flood severity index) and the area flooded showed to have no significant influence. These findings might suggest that individual flood risk perceptions are more effectively influenced by what individuals directly experience (i.e. amount of time being flooded, social interaction with affected individuals) other than what they indirectly experience (e.g. by scientifically based communications about events' severity or more abstract measures of flooding severity based on total area). Hence, individuals' flood risk adaptation behaviour seems to be influenced by direct experiences and interactions to a major extent and to a lesser extent by indirect communication about the events. Messner and Meyer (05) indicate that the level of information with respect to likely damage and vulnerability is crucial for changing persistent behavioural patterns of disaster risk adaptation. Kunreuther et al (85) already reported that considerable empirical evidence suggests that individuals are unwilling to protect themselves against low probability-high loss events even if the costs of protection are subsidized. This behavior is difficult to rationalize using the traditional expected utility model.

(iii) *General Climate Change* : General climate dynamics (measured by temperature, precipitation, and number of rain days per year) show a positive and significant effect on individuals' relative risk premia. The dynamic panel estimates reveal that the more severe temperature levels vary, the higher the level of precipitation, and the more rain days per year the higher the individual risk premium. These findings suggest that farmers located in high flood risk areas to a certain extent perceive the risk related to natural disasters also as a consequence of climate dynamics.

(iv) *Policy* : Policy changes with respect to flooding prevention and damage mitigation showed a risk premium decreasing effect in 1998 and 2007, however, a risk premium increasing effect for 2008. In 1998 policies that sought to improve and modify the system of flood warnings and public awareness raising were accelerated and implemented (Johnson et al 05). Based on the Bye Report a national and clearly defined four level system of flood warning codes with associated behavioural advice was developed. The Environment Agency further developed a multi-media warning dissemination service with the capacity to deliver a larger number of warning messages. In 2007 the EU Floods Directive has been introduced (2007/60/EC) requiring a consolidated river basin management planning, assessment and mapping of hazards and risks as well as preparation and use of flood risk management plans at member states level. Following the 2007 floods the Pitt Review in 2008 made 92 recommendations on improving the flood risk management in the UK. This review identified clear gaps in the way that flood risk is managed, particularly in relation to surface water and groundwater flooding. Further this report identified the need to adapt to climate change which is predicted to increase flood and coastal erosion risks. The UK government implicitly acknowledged these crucial reform needs by publishing a new Floods and Water Management Bill in the same year. Controlling for other flood risk related policies, actual flood events as well as general climate change related developments the estimates indicate that the policy measures in 1998 and 2007 might have led to a perceived lower risk of flooding among farmers in high flood risk areas whereas the published review in 2008 might have demonstrated existing shortcomings leading to the perception of higher risk.

(v) *Business and Socioeconomic Characteristics* : The estimates suggest that farms with higher total output but also higher profit per ha exhibit a higher risk preference towards flooding. The economic capacity of firms and households has been acknowledged in the literature as a major factor for differences in adjustment patterns (e.g. Smith et al 06). The same holds for irreversibilities with respect to agricultural capital infrastructure. Hence, those farms achieving a higher output might be those with higher adjustment costs in the case of flooding as a result of such irreversibilities. On the other side, off-farm income was found to negatively influence the individual risk premium with respect to flooding risk. This could suggest that those farmers feel less dependent on their agricultural income, hence, their risk preference towards the risk of flooding seems to be less pronounced. Testing for a difference in risk preferences towards flooding with respect to the dominat type of crop production on the farm, the estimates revealed that those mainly engaged in cereal production show a significantly higher risk preference towards flooding than those engaged in general cropping activities. Finally, the age of the farmer showed to be significant for his risk attitudes towards natural disasters: younger farmers tend to have higher risk preferences towards flooding. Kenyon et al (08) conclude that the low uptake of adaptation management options is predominantly due to a lack of advice and prevailing attitudes among farmers. Hence, it might be the case that the level of information with respect to likely damage and vulnerability is higher among younger farmers whereas such information is crucial for changing persistent behavioural patterns of disaster risk adaptation.

Risk Preference Scenarios

As outlined above, the specific flood policy design should be also a function of farmers' production technology but also their risk preferences. These preferences define the way the farmers use inputs to hedge against production risk, adopt mitigation technologies and mechanisms as well as adjust their production decisions over time to changing probabilities of extreme events. Using the estimated profit moments and risk premia, the substitution elasticities between all inputs K are evaluated to investigate the impact of different risk assumptions on the input choices of flood policy recipients (see table 4). The policy relevance of the farmers' risk preferences for the evaluation of flood policy measures can be illustrated by using the following example: The UK Country Land and Business Association (CLA) lobbies for the protection of high quality land to be protected to ensure food security. Essential claims are the management of the realignment of coasts and rivers under voluntary agreements with landowners, and allowing landowners to maintain sea walls and fluvial defences (see CLA 08). The cost-effectiveness of such measures is based on the optimisation behaviour of the individual landowner, hence, his relative input choices subject to his underlying risk preferences. E.g. the willingness to use more labor instead of other inputs to maintain such flood defences is based on the individual farmers profit function and hence, the substitution elasticities between labor and other inputs.

(Table 4 about here)

Scenario I: We assume that farmers in high flood risk areas are risk neutral and simply attempt to maximize profit (column I in table 4). The elasticities' estimates for this scenario show that farmers would substitute 1% more labor for 0.29% less capital and for 0.19% less chemicals, however, would complement the use of 1% more labor by the use of about 0.09% more intermediate inputs (i.e. energy, water etc.)[5] *Scenario II*: We assume that farmers in high flood risk areas have preferences over the variance of profit (column II in table 4). The elasticities' estimates show that under this assumption farmers would substitute 1% more labor for 0.27% less capital and for 0.37% less chemicals but would complement the use of 1% more labor by the use of about 0.07% more intermediate inputs. *Scenario III*: We assume that farmers in high flood risk areas have preferences over both the variance and skewness of profit (column III in table 4). Here, farmers would substitute 1% more labor for 0.21% less capital and for 0.25% less chemicals but would complement the use of 1% more labor by the use of about 0.10% more intermediate inputs.

Overall, it can be concluded that farmers in high flood risk areas would substitute about 30% less capital but about 30% more chemicals for using labor to maintain flood defences under the assumption of full risk preferences. Also, those farmers would incur additional costs of about 11% for the use of complementing intermediates compared to the case of risk neutrality. The significant differences between the scenarios analysed come from the fact that under risk-neutrality inputs' reallocation is only determined by technological constraints, whereas under full risk-aversion landowners reallocate inputs by considering also risk hedging possibilities (Leathers and Quiggin 91, Groom et al 08). Policy makers (but also interest groups etc.) who ignore these factors for individual flood adaptation and mitigation decision-making will design (and suggest) inefficient and probably ineffective flood policies leading to negative welfare effects (approximated by the relative risk premia) via the erroneous prediction of external effects. In the case of the discussed example above this could result in a much higher uptake of such defence measures offered under voluntary agreements as e.g. the required capital substitute by the average farm located in high flood risk areas is far less than anticipated by the policy maker, hence, irreversibilities might be less important for the farmer's decision.

[5] Note that the substitution elasticities are not symmetric in this case as the risk related parameters differ in value and sign across inputs.

7 - Conclusions

This paper suggests a microeconometric method for measuring flooding related risk preferences among individual farmers and landowners based on a flexible method of moments approach. Risk preferences of crop farmers located in areas of the UK characterised by a high risk of flooding are estimated. To ensure the absence of selectivity bias we follow a quasi-experimental research set-up using a sequence of flooding events and a control sample of crop farms located in areas of the UK characterised by a low risk of flooding. By using a comprehensive panel dataset for 28 years supplemented by flooding events and general climate change related data we improve on earlier contributions by investigating in a second step also potential factors for dynamics in relative risk premia at indvidual level controlling for potential behavioural lags and endogeneity of preference explaining factors. Furthermore, we discuss the importance of considering individual risk preferences for an efficient flood policy design using the example of voluntary agreements with landowners for maintaining flood defences. To our knowledge this contribution represents the first empirical approach to measure flooding risk related individual preferences and disentangle potential factors for changes in these preferences over time.

The findings of this study have crucial implications for the future design of natural disaster related mitigation and adaptation policies. At the time of completing this empirical investigation the first parts of the UK Flood and Water Management Act 2010 have been implemented based on the Pitt review for the 2007 floods (The Pitt Review 07). However, as has been the case for previous flooding policies this Act does not consider the individual risk attitudes of policy recipients towards flooding, let alone heterogeneity of such attitudes among recipients. The findings of this empirical study show that policies neglecting such individual risk preferences most likely result in inefficient and suboptimal outcomes.

Future research is needed, e.g. to establish a link between risk proxies at individual level based on revealed and stated preference methods' in order to confront actual perceptions about flooding risk with estimated preferences based on observed behavioural responses to past events.

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Table 1 Risk Estimates

Parameter	**Sample 1: Significant Flood Risk**	**Sample 2: Insignificant Flood Risk**
capital		
φ_{1c}	0.0244*** (0.001)	0.0046*** (0.002)
ap (*based on* φ_{2c})	3.6842*** (0.0089)	1.0718*** (0.031)
ds (*based on* φ_{3c})	19.1873*** (0.046)	-2.3453*** (0.001)
labor		
φ_{1l}	0.0137*** (0.003)	0.0058*** (5.94e-05)
ap	2.7248*** (0.055)	-0.4641*** (0.023)
ds	-11.4331*** (0.007)	-13.1441*** (0.027)
intermediates		
φ_{1i}	0.1332*** (0.003)	0.0175* (0.0103)
ap	5.3598*** (0.014)	-6.6747*** (0.008)
ds	10.6599*** (0.002)	-11.8884*** (0.008)
chemicals		
φ_{1ch}	0.0062*** (7.42e-05)	-0.0042** (0.002)
ap	2.1227*** (0.011)	-2.2409*** (0.001)
ds	3.4607*** (0.001)	-3.7749*** (1.33e-05)
risk premium		
rrp (rp/E(π))	0.0782*** (0.008)	0.0191** (0.009)
+ 1 standard deviation	0.0875	0.0326
- 1 standard deviation	0.0689	-0.0037
observations	5811	7147

SE in parentheses (based on bias-corrected bootstrapped standard errors); ***,**,*: significance at 1, 5, 10%-level.
ap: Arrow-Pratt risk coefficient;
ds: down-side risk coefficient; estimates are based on a random-effects estimation of a profit function model and a random-effects estimation of a seemingly unrelated system of equations for the risk moments.

Table 2 Estimates – DPD Risk Premium Model (Significant Flood Risk Sample)

Parameter	Estimate (SE)	Parameter	Estimate (SE)
Lagged Variables		***Exogenous Variables***	
risk premium t-1	0.3333*** (0.0142)	*III) General Climate Parameters*	
risk premium t-2	0.0881*** (0.0303)		
Endogenous Variables		maximum yearly temperature	0.0363** (0.0161)
I) Major Flooding Events		minimum yearly temperature	-0.0621*** (0.0187)
flooding 01/2008	0.1296*** (0.0681)	number of sun hours per year	-4.36e-05 (3.08e-05)
flooding 07/2007	0.4311*** (0.0704)	precipitation per year	9.39e-05** (4.41e-05)
flooding 06/2007	0.1968** (0.0632)	rain days per year	0.0022*** (0.0005)
flooding 08/2005	-0.7647 (1.0103)		
flooding 06/2005	-0.0048 (0.0425)	*IV) Flooding Policy*	
flooding 02/2004	0.0215 (0.1011)	flood policy change 1998 [2]	-0.0423*** (0.0079)
flooding 01/2003	0.0313*** (0.0035)	flood policy change 2000	0.0034 (0.0077)
flooding 08/2002	-0.0356 (0.0714)	flood policy change 2004	-0.0106 (0.0081)
flooding 10/2001	-8.03e-04 (0.0243)	flood policy change 2006	0.0066 (0.0103)
flooding 11/2000	0.1183*** (0.0101)	flood policy change 2007	-0.1712*** (0.01633)
flooding 10/2000	-0.0024 (0.0324)	flood policy change 2008	0.1175*** (0.0202)
flooding 12/1999	0.0408** (0.0225)		
flooding 03/1999	0.0561 (0.0639)	*V) Farm and Farmer Characteristics*	
flooding 10/1992	0.0202 (0.0203)	total output	6.13e-08** (3.16e-08)
flooding 09/1992	0.2606* (0.1459)	farm type [3]	-0.0715*** (0.0093)
flooding 08/1992	0.0645 (0.0761)	altitude [4]	-0.0233 (0.0187)
flooding 07/1992	-5.28e-03 (0.0866)	age of farmer	-5.62e-06*** (3.64e-05)
flooding 12/1990	-0.03772 (0.8157)	education [5]	9.94e-04 (0.0033)
flooding 10/1990	0.3497*** (0.1404)	off-farm income	-1.15e-07*** (1.37e-08)
flooding 01/1990	0.2662 (0.2304)	form of business [6]	-0.0021 (0.0044)
II) Flooding Characteristics		profit per ha	0.0001*** (1.91e-06)
days flooded per year	0.0742*** (0.0084)		
km^2 flooded per year	-2.41e-06 (1.63e-06)	constant	-0.2143** (0.1081)
severity of flooding per year [1]	-0.0117 (0.0089)		
density of affected farms [7]	0.7326*** (0.3368)	*observations*	5811

SE in parentheses (based on robust standard errors); ***,**,*: significance at 1, 5, 10%-level; Estimates are based on a robust dynamic panel estimation using the Arellano-Bover/Blundell-Bond linear dynamic panel-data estimator (GMM type); Instruments for endogenously determined regressors: exogenous regressors under III) general climate parameters and IV) flooding policy. **1** - severity classes: class 1 - large flood events: significant damage to structures or agriculture, fatalities, and/or 1-2 decades-long reported interval since the last similar event; class 1.5 - very large events: greater than 20 yr but less than 100 year recurrence interval, and/or a local recurrence interval of at 10-20 yr; class 2 - Extreme events: with an estimated recurrence interval greater than 100 years (source: http://www.dartmouth.edu/~floods/Archives/index.html). Average severity of flooding events per year if more than one event. **2** – flooding policy: 1998 – UK improvement and modification of flood warning system and general public awareness rise; 2000 – EU Water Framework Directive/WFD (2000/60/EC); 2004 – UK Floodline Warnings Directive (FWD); 2006 – UK Planning Policy Guidance (PPG) 25 governmental guidance; 2007 - EU Floods Directive; 2008 - UK Pitt report. **3** - farm type: 0 - cereals, 1 - general cropping; **4** - altitude: 0 - most of holding below 300m, 1 - most of holding at 300m or over; **5** - education: 0 - school only, 1 - GCSE or equivalent, 2 - A level or equivalent, 3 - College/National Diploma/Certificate, 4 - degree, 5 - postgraduate qualification, 6 - Apprenticeship, 9 - other; **6** - form of business: 1 - sole trader, 2 - partnership(family), 3 - partnership(other), 4 - farming company, 5 - other; **7** - number of farms affected by flooding events as share of total number of farms in high flood risk areas.

Table 3 Marginal Effects of Inputs on Profit Distribution

Parameter	Sample 1: Significant Flood Risk	Sample 2: Insignificant Flood Risk
$\partial E(\Pi)/\partial Capital$	0.058** (0.029)	0.0509** (0.010)
$\partial E(\Pi)/\partial Labor$	0.204*** (0.042)	-0.003*** (3.56e-04)
$\partial E(\Pi)/\partial Intermediates$	0.921*** (0.0184)	0.630*** (0.007)
$\partial E(\Pi)/\partial Chemicals$	-0.0539* (0.031)	-0.129* (0.026)
$\partial E(\Pi)/\partial Time$	0.009*** (7.06e-04)	0.029*** (0.001)
$\partial Var(\Pi)/\partial Capital$	-0.007 (0.009)	-0.006* (0.012)
$\partial Var(\Pi)/\partial Labor$	-0.021*** (0.006)	-0.002*** (2.35e-04)
$\partial Var(\Pi)/\partial Intermediates$	0.189*** (0.006)	0.136*** (0.005)
$\partial Var(\Pi)/\partial Chemicals$	-0.009 (0.011)	0.067*** (0.015)
$\partial Var(\Pi)/\partial Time$	4.714e-04** (2.33e-04)	0.003*** (6.82e-04)
$\partial Ske(\Pi)/\partial Capital$	-0.008 (0.013)	-0.025 (0.018)
$\partial Ske(\Pi)/\partial Labor$	-0.024*** (0.019)	-0.002*** (3.59e-04)
$\partial Ske(\Pi)/\partial Intermediates$	0.096*** (0.008)	0.058*** (0.007)
$\partial Ske(\Pi)/\partial Chemicals$	-0.003 (0.015)	0.026 (0.023)
$\partial Ske(\Pi)/\partial Time$	3.827e-04 (3.14e-04)	0.001 (0.001)

SE in parentheses (based on the delta method); ***,**,*: significance at 1, 5, 10%-level; 'E' – expected profit, 'Var' – variance of profit, 'Ske' – skewness of profit. inputs

Table 4 Scenarios - Input Elasticities at Sample Means (Significant Flood Risk Sample)

Input Elasticity (X_K/X_{K-1}) [1]	Scenarios I) Risk Neutrality (ap = ds = 0)	II) No Down-Side Risk (ds = 0)	III) Full Risk Preferences (ap, ds as estimated)
Capital/Labor	-0.8491*** (0.2843)	-0.7309*** (0.2474)	-0.5786* (0.3327)
Capital/Intermediates	0.5878** (0.2943)	0.9391** (0.4529)	0.8749 (0.6129)
Capital/Chemicals	-0.6899** (0.3083)	-0.5843** (0.2785)	-0.7874** (0.4008)
Labor/Capital	-0.2923*** (0.0887)	-0.2706*** (0.0806)	-0.2122*** (0.0655)
Labor/Intermediates	0.0901** (0.0313)	0.0717*** (0.0266)	0.1028*** (0.0270)
Labor/Chemicals	-0.1938** (0.0986)	-0.3686*** (0.0956)	-0.2471*** (0.0866)
Intermediates/Capital	0.7561*** (0.0721)	-0.3484*** (0.0224)	-0.2405*** (0.0139)
Intermediates/Labor	0.1889*** (0.0424)	0.0322*** (0.0117)	0.0047 (0.0079)
Intermediates/Chemicals	0.2364** (0.1135)	-0.0373 (0.0309)	0.1988*** (0.0226)
Chemicals/Capital	0.1065 (0.0910)	0.0987** (0.0392)	0.1425 (2.4161)
Chemicals/Labor	0.8702 (0.8651)	0.2736 (5.3866)	0.2594 (4.3645)
Chemicals/Intermediates	-0.4999 (0.4499)	0.1921 (0.2379)	-0.5355 (0.4732)

SE in parentheses (based on robust standard errors); ***,**,*: significance at 1, 5, 10%-level. Estimates are based on the Delta method evaluated at sample means and correspond to a 1% change in X_{K-1}. 1: note that the values of these risk based elasticities are only symmetric across inputs if the risk related parameters are the same in value and sign across inputs.