To risk or not to risk? Risk management and farm productivity

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Abstract: The impact of risk management on farm productivity is still being debated. Using survey data from French and Hungarian farms, we estimate the impacts of different risk management strategies and portfolios under varying levels of risk on total factor productivity. Results from a multinomial endogenous switching regression model show that the impacts can be positive or negative, depending on the risk management strategies adopted, the structure of the farming system and the probability of risks. The choice of risk management strategies influences the farm's production costs and the allocation of resources. More complex risk management portfolios tend to have larger negative productivity impacts due to higher costs and the larger amount of resources subtracted from the production activity. Our results have important implications for risk management policies.

Keywords: multinomial endogenous switching regression, risk management, risk probability, total factor productivity, wheat

JEL codes: G22, G32, Q12, Q18

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Farmers use risk management to cope with unexpected natural and market risks and to mitigate potential negative effects of changing environmental conditions (Tangermann 2011; Challinor et al. 2014). Public expenditures on agricultural risk management policies are substantial in many developed countries, and the European Union (EU) is currently giving risk management a more prominent role in its Common Agricultural Policy (CAP). However, the impact of risk management practices on productivity is still being debated (Glauber 2004; Kim et al. 2012; Cornaggia 2013). Some risk management strategies (e.g. insurance) may reduce uncertainty and thus lead to larger investments, which can enhance productivity (Rakotoarisoa 2011; Carter, Cheng and Sarris 2016; Trujillo-Barrera et al. 2016). Other risk management strategies may affect productivity more directly, for example, diversifying the portfolio of crop varieties can increase or decrease overall productivity (Di Falco and Chavas 2006). Risk management often also comes with a cost to farmers, increasing production costs and reducing productivity (Ahsan, Ali and Kurian 1982; Vigani, Rodriguez-Cerezo and Gomez-Barbero 2015).

This paper examines the question of how common risk management practices affect productivity. Studies addressing this issue are still scarce. So far, the literature on agricultural risk management has focused on the drivers of adopting risk management strategies, mainly looking at crop, weather and revenue insurance (Mishra and El-Osta 2001; Sherrick et al. 2004; Velandia et al. 2009; Enjolrasa and Sentis 2011; Chakir and Hardelin 2011; Enjolras, Capitanio and Adinolfi 2012; Finger and Lehmann 2012; Santeramo et al. 2016), index insurance in developing countries (e.g. Cole et al. 2013; Cai et al. 2015; Jensen and Barrett 2017) and, to a lesser extent, diversification (Weiss and Briglauer 2000; Mishra and El-Osta 2002; Kim et al. 2012). Important research has been done on how the adoption of agricultural insurance affects production decisions and national production capacity by examining the acreage expansion of risky crops or livestock (e.g. Goodwin, Vandeveer and Deal 2004; Smith and Glauber 2012; Cai et al. 2015; Claassen, Langpap and Wu 2017; Yu, Smith and Sumner 2018). Other authors examined the effects of risk management (mainly insurance) on input use (e.g. see Glauber 2004 and Mieno, Walters, and Fulginiti 2018 for reviews of this literature), concluding that risk management negatively affects the use of risk-reducing inputs (e.g. pesticides) because of moral hazard problems (Goodwin 2001).

This article departs from the above literature and examines the implications of risk management for productivity due to resource allocation and cost decisions at the farm level. In doing so, the article builds on a rather new literature. Among the few studies investigating the effect of risk management on farm productivity, some are particularly relevant for our analysis. Di Falco and Chavas (2006) studied the impact of crop genetic diversity (sometimes called "natural insurance") on farm productivity, showing that in one Italian region and in a sample of 50 observations, crop genetic diversity increased wheat yields and reduced risk exposure. Spörri et al. (2012) provided a larger analysis using farm accountancy data from Hungary, finding a negative impact of insurance on farm profit, labor and land productivity in arable farms. This negative impact can reduce the potential benefits derived from the income stabilizing effect of crop insurance through compensation payments. In contrast, Cornaggia (2013) found a positive relationship between insurance and crops yield in the US, which is however critically linked to the local availability of credit institutions. Finally, Matsushita, Yamane and Asano (2016) showed that in Japan, genetic diversity increases rice yields during good periods, but decreases yields during bad periods because the more complex field operations required for variety diversification are more difficult to manage during bad environmental conditions.

Although these four studies provide important results, they have some limitations, such as the use of partial measures of productivity (e.g. yield) and the focus on single risk management strategies (financial or natural insurance). Moreover, with the exception of Matsushita, Yamane and Asano (2016), they disregard the link between the benefits of risk management and the probability of risks.

Our research goes beyond these limitations in the literature. We examine the case of wheat in the EU, which is the most important producer and exporter globally but is experiencing stagnating productivity (Vigani, Dillen and Rodriguez-Cerezo 2013). We focus on two countries: France, the biggest wheat producer in the EU and representing a group of countries with high yields and advanced technology; and Hungary, representing a second group of countries with significantly lower wheat yields and a more heterogeneous farm structure (Vigani, Rodriguez-Cerezo and Gomez-Barbero 2015). Using survey data of 700 farmers, we estimate the impact of risk management through multinomial endogenous switching regression (MESR) and a semi-parametric measure of total factor productivity (TFP). Using TFP has the advantage of incorporating both observed and unobserved resources and management costs. In addition to the average treatment effect on the treated, we also calculate first and second differences between high and low risk farms.

We analyze a comprehensive set of risk management portfolios based on crop insurance, production contracts, production diversification and genetic diversity (i.e. use of multiple varieties), which are the most common risk management tools in our dataset. Different combinations of the four tools generate sixteen risk management portfolios. Analyzing multiple portfolios is particularly sensible in the EU context, because markets and policies of risk management tools such as agricultural insurance and futures contracts are less developed than in other countries (e.g. the US). Therefore EU farmers are more oriented towards individually adopting a combination of on-farm risk management strategies (Enjolras, Capitanio and Adinolfi 2012).

Our results show that risk management significantly affects TFP, negatively or positively depending on the risk management portfolio and the level of risks. More complex risk management portfolios composed of a combination of different risk management tools tend to have larger impacts. This is particularly observed for higher-risk farms. Our results have important implications for policy planning and budget allocation towards risk management tools.

Theoretical background

Following Schmit and Roth (1990, pp. 457), we define risk management as “the performance of activities designed to minimize the negative impact of risks regarding possible losses. Because risk reduction is costly, minimizing the negative impact will not necessarily eliminate risk. Rather, management must decide among alternative methods to balance risk and cost, and the alternative chosen will depend upon the organization's risk characteristics”. In order to mitigate the negative impact of (natural and market) shocks, a risk-averse farmer shifts part of his (financial and/or management) resources from production activities to risk management. The modified allocation of resources and inputs use can thus alter farm output.

The farm’s allocation of productive resources under different levels of risks and the impact of costly risk management on a farm’s output can be described with the one input and one output model proposed by Ahsan, Ali and Kurian (1982), which considers a farm with a limited endowment of production factors.

In this model, a farm without risk management faces two states of nature. The first state is characterized by good natural conditions and the farm not adopting risk management retains its entire output – i.e. there are no crop losses (good state). The second state is characterized by adverse natural conditions (e.g. hail, drought and flood) and the farm loses the entire output (bad state). The farm also has the choice between a risky and a riskless production, with the following conditions: i) the risky production has positive but decreasing marginal productivity; ii) the riskless production has a constant rate of return; iii) the expected marginal product of the risky production exceeds the one of the riskless production.

Given these conditions, a share of the production factors is devoted to the risky production and the rest to the riskless one. These resources are subtracted from the overall endowment of the farm's production factors. Different types of risky production will require different shares of resources. Because the constrained production factors are allocated between risky and riskless production and because the two alternatives have different marginal productivity, the balance between the two will affect the total output of the farm.

A farm adopting risk management faces the same two states of nature (good and bad natural conditions) but, in addition to the allocation of resources between risky and riskless production, adopters have to consider also the cost associated with risk management. The cost of managing risks varies depending on the risk management strategy and comprises observable costs (e.g. insurance premium, contracts costs) and unobservable costs (e.g. costs to gather and analyze information on risks). Both observable and unobservable costs increase with the complexity of risk management.

If the farmer is risk averse, he will choose full adoption of risk management to avoid crop failures. When full adoption of risk management is chosen, the farmer can choose any input level as if he was risk neutral. In other words, by adopting risk management, the risk adverse farmer behaves as a risk taker reallocating resources to the risky activity, while facing the cost of risk management.

This basic model has been extended by Nelson and Loehman (1987) to multiple inputs and outputs, showing that the benefits of risk management can change depending on the nature of the inputs and outputs. With risk-increasing inputs (e.g. fertilizers), a farmer adopting risk management produces more output than a non-adopter; however, if the input is risk reducing (e.g. crop protection), the farmer not adopting risk management produces more output. In other words, risk management does not necessarily increase production. A risk-averse farmer will manage risks if, and only if, the expected utility with risk management is greater than the expected utility without risk management (Nelson and Loehman 1987).

A further extension is provided by Ramaswami (1993) who examined the impact of risk management on expected producer's supply – i.e. given that risk management affects farm income, producers adjust supply in response to this change. According to Ramaswami (1993), risk management can reduce the marginal productivity of inputs, because the production increase is accompanied by a decrease in expected returns from risk management. Therefore, the farmer can choose to reduce input use (maximizing the marginal returns from input use), which in turn can decrease output (Ramaswami 1993).

Following the theory on risk management adoption developed by the above mentioned authors, we developed three key hypotheses to drive our analysis:

H1: The reallocation of financial and managerial resources from production factors to risk management affects the productivity of the farm.

H2: The extent to which the reallocation of resources affects farm productivity depends on the complexity and costs of risk management.

H3: The impacts of risk management on productivity are larger in high risk conditions.

H1, *H2* and *H3* are tested empirically for the wheat sector in France and Hungary in the following sections of the paper.

Econometric strategy

The evaluation of the performance of risk management is complex because farmers make decisions under uncertainty. Following the theory on risk management and farm output (Ahsan, Ali and Kurian 1982; Nelson and Loehman 1987; Ramaswami 1993), our approach is to estimate the impact of the adoption of different risk management tools on the farm's performance (treatment effect), taking into account potential market uncertainties and different levels of production risk.

In order to study the impact of risk management on productivity, it is important to account for the potential reverse causality between the adoption of risk management and productivity (Ramaswami 1993). For example, more productive farms with higher returns are more likely to have the financial and managerial resources to afford (costly) risk management. The fact that the demand for risk management tools can be influenced by farm performance has been demonstrated in previous research (e.g. Mishra and El Osta 2002; Spörri et al. 2012; Cornaggia 2013). For instance, in Hungary, financial constraints can affect the purchase of insurance (Bielza Diaz-Caneja et al. 2009). A second potential source of endogeneity comes from the substitution effect between risk management and input use (Nelson and Loehman 1987). Fertilizer use can increase risk and thus be positively correlated with risk management, while crop protection reduces production risks and is negatively correlated with risk management (Goodwin, Vandeveer and Deal 2004).

Moreover, the farms deciding to adopt a particular risk management strategy are unlikely to be a random sample of the original population, because i) adoption is voluntary; ii) a particular strategy can be adopted by those who find it most useful (i.e. adopters can have systematically different characteristics and reasons to adopt than non-adopters). As a result, farmers adopting particular risk management strategies are likely to be self-selected, having common unobservable characteristics potentially affecting the adoption decision and the farm's performance, provoking inconsistent estimates of the impact of risk management on farm productivity (Di Falco and Veronesi 2013).

Another important issue to consider is that risk management decisions are made simultaneously. If we do not account for the fact that farmers can adopt several risk management strategies simultaneously, estimates can be biased as the overall effect is not necessarily equal to the sum of the effects of adopting each strategy separately (Wu and Babcock 1998). We consider the four risk management tools that are most frequently adopted in wheat farming in France and Hungary (insurance, diversification, multiple varieties and contracts) and which generate M=16 different combinations. Each combination represents a risk management portfolio.

The best strategy to obtain a treatment effect while controlling for endogeneity is to apply a simultaneous equations model of risk management adoption and farm productivity with multinomial endogenous switching regression (MESR), consisting of a two-stage process generating selection-corrected productivity outcomes (Bourguignon, Fournier and Gurgand 2007; Di Falco and Veronesi 2013).

We have also considered alternative approaches to MESR, but found them less suited for our analysis. Simple regression models fail to control for unobserved farm and farmer characteristics (e.g. farmers ability and motivation), which can be correlated with both farm productivity and risk management adoption and thus lead to selection bias (adopters and non-adopters may differ systematically) and biased treatment effects (Heckman 1979). Statistical methods that deal with selection bias include propensity score matching (PSM) and difference-in-differences (D-i-D) approaches. However, PSM only controls for observed heterogeneity and D-i-D would require data collected from both the treatment and control groups before and after risk management adoption, while our data is observational data collected after the risk management was used by a group of farmers.

MESR belongs to the category of instrumental variable (IV) approaches, which corrects for unobserved heterogeneity and selection bias. The advantage of MESR over other IV treatment effects models with one selection and one outcome equation is that MESR estimates as many simultaneous outcome equations as many risk management combinations are adopted, in combination with the selection equation (e.g. Wu and Babcock 1998; Di Falco and Veronesi 2013; Teklewold et al. 2013; Kassie et al. 2015).

First stage: multinomial selection model of risk management strategies

In the first stage, farm households face a choice of *M* mutually exclusive combinations of risk management tools. Each combination represents a different risk management portfolio.

Farmers aim to maximize their productivity by comparing the productivity provided by the *M* alternative portfolios. Assuming that the risk management portfolio preference of a farm operator is a function of exogenous variables and that the observations in the sample are independent, the different levels of productivity between farms adopting different portfolios is defined by the latent variable A_{ij}*:

(1) $$A_{ij}^{*} = \boldsymbol{Z_i \alpha_j} + \eta_{ij} \text{ with } A_i = \begin{cases} 1 \; iff \; A_{i1}^{*} > \max\limits_{k \neq 1}(A_{ik}^{*}) \text{ or } \varepsilon_{i1} < 0 \\ \vdots \quad \vdots \quad \vdots \\ M \; iff \; A_{iM}^{*} > \max\limits_{k \neq M}(A_{ik}^{*}) \text{ or } \varepsilon_{iM} < 0 \end{cases}$$

where

(2) $$\varepsilon_{ij} = \max_{k \neq j}(A_{ik}^{*} - A_{ij}^{*}) < 0$$

That is, the farm operator i will chose portfolio j if the expected productivity from the portfolio j is higher than the expected productivity from any other portfolio $k \neq j$.

The selection model has two components. A deterministic component $Z_i\alpha_j$ that affects the probability of choosing portfolio j through factors Z_i, such as observable farm and operator characteristics and risk factors. An idiosyncratic unobserved stochastic component η_{ij} capturing unobservable factors, such as administrative and management costs associated with the use of risk management portfolios, and other intangible costs linked with the adoption decision (e.g. use of advanced analytical tools for risk management decisions and time spent on gathering information). These unobserved costs may vary depending on the risk management portfolio adopted. For instance, insurance is associated with benefits such as reduced contracting cost, reduction in the cost of bankruptcy, and lower taxes (Schmit and Roth 1990).

The parameters of the latent variable model can be estimated by maximum likelihood. Assuming that η_{ij} is identically and independently Gumbel distributed (the independence of irrelevant alternatives (IIA) hypothesis), the probability P_{ij} that the farm operator i with characteristics Z_i will choose risk management portfolio j can be specified as a multinomial logit model (McFadden 1973):

(3) $$P_{ij} = P\left(\varepsilon_{ij} < 0 \middle| \boldsymbol{Z}_i\right) = \frac{\exp(\boldsymbol{Z_i\alpha_j})}{\sum_{k=1}^{M}\exp(\boldsymbol{Z_i\alpha_j})}$$

The main limitation of estimating a multinomial logit model is the IIA assumption, which is that the relative probabilities of choosing any alternative portfolio are independent of the other choices available, putting restrictions on the farmer's behavior (Wu and Babcock 1998). However, the approach taken by Bourguignon, Fournier and Gurgand (2007) shows that using the multinomial logit model provides robust selection bias correction for the outcome equation, even if the IIA hypothesis is violated (Teklewold et al. 2013).

Second stage: multinomial endogenous switching selection model

In the second stage, the effects of different risk management portfolios on farm performance are estimated.

The difficulty in measuring the costs associated with risk management also drives the choice of the outcome variable. Previous studies used yields as a measure for farm productivity (e.g. Di Falco, Veronesi and Yesuf 2011; Spörri et al. 2012; Cornaggia 2013) which is a measure of partial, and more specifically, land productivity. Risk management concerns not only land but also additional production factors, especially intangible ones like managerial capacity and knowledge. This implies that the farm needs to be acknowledged as a productive system able to shift resources across different production activities, rather than a productive unit with fixed allocation of inputs. Therefore, we need to use a measure of total factor productivity (TFP), which considers all the production factors that can be involved both in the production activity and in the management of risks, such as labor allocation and assets, and not only direct production inputs.

We estimate TFP using the semi-parametric procedure proposed by Levinson and Petrin (2003) (LP). One problem during the estimation of production functions is the correlation between unobservable productivity shocks and input levels, i.e. profit-maximizing firms responding to positive productivity shocks by expanding output, which requires additional inputs, and *vice versa*. The LP approach has two advantages. First, it adjusts for unobservable productivity shocks by using intermediate inputs as a proxy. Second, the TFP is estimated as a latent variable, which can be interpreted as the unobservable (technical or management) innovation and quality level of the farm (Curzi and Olper 2012) (see the supplementary appendix I online for details on TFP estimation and results).

The outcome equation for each possible risk management portfolio j is given as:

$$(4) \qquad \begin{cases} \text{Regime 1: } y_{i1} = \boldsymbol{X_i \beta_1} + u_{i1} \ \text{ if } \ A_i = 1 \\ \qquad \vdots \qquad\qquad\qquad\qquad \vdots \\ \text{Regime } M\text{: } y_{iM} = \boldsymbol{X_i \beta_M} + u_{iM} \ \text{ if } \ A_i = M \end{cases}$$

y_i is the level of farm productivity (outcome variable) in regime 1 (no risk management portfolio) to 16, $\boldsymbol{X_i}$ represents a vector of exogenous variables thought to influence farm productivity and u_i are random errors.

If the error terms of the selection equation (1) ε_i are correlated with the error terms of the outcome equation (4) u_i, OLS estimates of (4) are inconsistent and correction is needed. However, in order to use the multinomial logit as a selection bias correction model additional hypotheses are necessary. Approaches have been proposed by Lee (1983), Dubin and McFadden (1984) and Dahl (2002). The first impose quite restrictive assumptions on the covariance between ε_i and u_i, the second restricts the type of allowed distributions for ε_i and u_i, while the third depends on the stronger hypothesis/stronger precision arbitrage (Bourguignon, Fournier and Gurgand 2007). We apply the approach of Bourguignon, Fournier and Gurgand (2007) which modifies the assumption of Dubin and McFadden (1984), allowing a set of normal distributions (Bourguignon, Fournier and Gurgand 2007).

According to Bourguignon, Fournier and Gurgand (2007), equation (4) can be corrected in the following way:

$$(5)\qquad \begin{cases} \text{Regime 1: } y_{i1} = \boldsymbol{X_i \beta_1} + \sigma_1 \lambda_1 + \omega_{i1} \ \text{ if } A_i = 1 \\ \qquad\vdots \qquad\qquad\qquad\qquad \vdots \\ \text{Regime } M\text{: } y_{iM} = \boldsymbol{X_i \beta_M} + \sigma_M \lambda_M + \omega_{iM} \ \text{ if } A_i = M \end{cases}$$

where σ_j is the covariance between ε_i and u_i, ω_i is an error term with expected value of zero and λ_j is the inverse Mills ratio calculated from the probabilities estimated in (3) as:

$$(6)\qquad \lambda_M = \rho_M m(P_{iM}) + \sum_{k=1\ldots M-1}^{M} \rho_k m(P_{ik}) \frac{P_{ik}}{(P_{ik}-1)}$$

where ρ_i is the correlation coefficient of ε_i and u_i.

In this multinomial choice setting the number of selection correction terms generated is $M - 1$, one for each alternative risk management portfolio. In order to account for the heteroskedasticity arising from the generation of λ_j, the standard errors in (5) are bootstrapped.

Moreover, for the MESR model to be correctly identified it is important to follow the order condition that $\boldsymbol{Z_i}$ contains at least one variable not in $\boldsymbol{X_i}$. These additional variables need to be valid instruments correlated with the selection variable (adoption of risk management portfolios) but uncorrelated with y_{i1} (the TFP of non-adopters of risk management). These conditions for the instruments can be tested (see the supplementary appendix II online).

Counterfactuals and treatment effect estimations

The MESR can be used to compare the expected TFP of farms adopting different risk management portfolios. Given that we do not have information about the same farm passing from non-adopting to adopting risk management, or passing from a risk management portfolio to another, for the calculation of treatment effects we need to estimate counterfactuals for the treated (adopters of a risk management portfolio). In our case, we have *j*=2...16 different risk management portfolios, and *j*=1 is the reference category "no risk management". With the coefficient estimates of the MESR model we obtain the following expected TFP across real and counterfactual scenarios:

Adopters with adoption (actual adoption observed in the sample):

(a) $$E(y_{iM\neq1}|A_i = M_{\neq1}) = \boldsymbol{X_i\beta_{M\neq1}} + \sigma_{M\neq1}\lambda_{iM\neq1}$$

Non-adopters without adoption (actual non-adoption observed in the sample):

(b) $$E(y_{1i}|A_i = 1) = \boldsymbol{X_i\beta_1} + \sigma_1\lambda_{i1}$$

Adopters deciding not to adopt (counterfactual):

(c) $$E(y_{1i}|A_i = M_{\neq1}) = \boldsymbol{X_i\beta_1} + \sigma_1\lambda_{iM\neq1}$$

Non-adopters deciding to adopt (counterfactual):

(d) $$E(y_{iM\neq1}|A_i = 1) = \boldsymbol{X_i\beta_{M\neq1}} + \sigma_{M\neq1}\lambda_{i1}$$

The expected outcome can be used to obtain unbiased treatment effects on the treated (TT) as the difference between (a) and (c), controlling for observed and unobserved heterogeneity[1]:

(7) $$TT = E(y_{iM\neq1}|A_i = M_{\neq1}) - E(y_{1i}|A_i = M_{\neq1}) = \boldsymbol{X_i(\beta_{M\neq1} - \beta_1)} + \lambda_{1i}(\sigma_{M\neq1} - \sigma_1)$$

By creating different groups of farmers, we obtain an unbiased estimate of the impact of risk management on the TFP of farms in France and Hungary and of high and low risk farms. High and low risk farmers are defined empirically through the farmers' answers to the question "Which of the following natural disasters (hail, storm, flood, drought) happened to your wheat production in the last three years?". Because natural hazards are spatially distributed, we assume that the probability of climatic disasters is correlated with the farm location and that the probability of a disaster occurring is higher when it happened in the past (Vinet 2001). Therefore, we define high risk farms (*hr*) those who have suffered of at least one natural disaster in the last three years from the data collection; low risk farms (*lr*) if they did not suffer from natural disasters in the last three years.

We calculate also first differences between high and low-risk farms:

i. The difference in productivity between high and low-risk adopters, (a)*hr* - (a)*lr;*

ii. The difference in productivity between high and low-risk non-adopters, (b)*hr* - (b)*lr;*

iii. The difference in productivity between high and low-risk adopters in the counterfactual situation that they decided not to adopt, (c)*hr* - (c)*lr;*

Finally, we want to understand if changes in TFP are larger (or lower) in high or in low risk situations among adopters. We obtain this information by calculating the second difference (difference in difference) between treated high and low-risk farms as TT*hr* – TT*lr*.

Data description

The data used for the analysis come from a survey of 700 wheat farmers (350 in France and 350 in Hungary) and three wheat-growing seasons: 2010/2011, 2011/2012 and 2012/2013. A representative sample was drawn from a population defined as those farmers who grew wheat in 2012/13 and with an agricultural area of at least two hectares. A stratified multi-stage sample design with random selection of the final sample units was employed (see supplementary appendix III online for technical information about the survey). The most important wheat areas in both countries were selected and interviews allocated accordingly. The areas comprise the Paris Basin in France (Champagne-Ardenne, Picardie, Centre, and Bourgogne) and most regions of Hungary except the Northwest (Central, Western and Southern Transdanubia, as well as the Northern and Southern Great Plains).

Farmers were identified through different contact points; in Hungary through local agrarian offices and in France through pre-existing statistics and databases. Quotas were used to ensure a representative distribution of farm sizes in the sample. The sampling errors were 8.7% in France and 7.9% in Hungary, which are within the commonly accepted 10% for the confidence level of 95.5%.

Empirical specification

Descriptive statistics of the variables used in the econometric model are shown in Table 1.

The dependent variable (y_i) is the TFP of wheat farming for three growing seasons in the period 2010-2013, estimated as in Levinson and Petrin (2003). The supplementary appendix I online provides details on the TFP estimation. On average, French farms have higher TFP than Hungarian farms. French farms have a long tradition in growing wheat and have a larger share of income reinvested in the farming activity, which can explain greater and more fine-tuned productive assets. Selection variables (A_i) reflect the risk management portfolios adopted in both countries. Portfolios are described in Table 2 and consist of combinations of up to four risk management tools. The first one is crop insurance. There is not yet a common EU policy on agricultural insurance and each Member State has developed its own insurance market. In the case of France and Hungary, crop insurance pays indemnities when the crop has been hit by a natural disaster, most frequently hail, alleviating the effects of a severe drop in farm revenues (Vigani, Rodriguez-Cerezo and Gomez-

Barbero 2015). However, when compensation is not paid, the insurance premium can represent a net cost from the farm account balance (van Asseldonk et al. 2016). The second risk management tool is diversification of farming activities – i.e. if the farm combines the production of wheat with at least one additional horizontal or vertical activity. By horizontally (e.g. agro-tourism, livestock production) or vertically (e.g. process, distribute) diversifying income-generating farm activities, low crop revenues can be offset by higher revenues in other activities, stabilizing overall income (Meuwissen, van Asseldonk and Huirne 2008). The variance of income decreases with the increase in the number of activities engaged by the farm, however at a progressively diminishing rate (Berg and Kramer 2008). Nevertheless, farm diversification can be also associated with lower productivity and higher costs (e.g. additional equipment, loss of economies of scale and specialization) (Bielza Diaz-Caneja et al. 2009). The third risk management tool concerns wheat varietal diversity, identified by a binary variable equal to 1 if more than one wheat variety is cultivated. Cultivating wheat varieties with different genetic characteristics works as a portfolio insurance against extreme biotic or abiotic stresses (Matsushita, Yamane and Asano 2016), reducing the risk of yield variability and crop failure, while improving crop resilience and average productivity (Di Falco and Chavas 2006). However, an excessive number of varieties can reduce farm efficiency due to production fragmentation, segregation costs and cultivation of lower yielding varieties on part of the farm surface. Finally, the fourth risk management tool is production contracts. Production contracts are risk-sharing tools stipulated between farms and purchasers (e.g. processors, retailers, cooperatives) to reduce market risks by setting the price in advance and/or by ensuring market access (Palinkas and Székely 2008). Production contracts can also facilitate the diffusion of innovative practices or quality standards by means of transferring information between the agribusiness sector and farmers (Eaton and Shepherd 2001). However, contracts can apply pricing matrix systems[2] which reduce farmers' incentives to produce higher volumes more efficiently.

By combining these four risk management tools, a total of sixteen risk management portfolios are obtained (table 2). Almost 7% of the farmers in our dataset exhibit a risk taking behavior by not adopting any of the major risk management tools (portfolio 1). This choice is more frequent in Hungary, while less than 0.5% of French farmers did not adopt any of the major risk management tools. Overall, the frequency of French farmers adopting a single tool is lower than in Hungary. In particular, contract farming in France is always combined with at least an additional tool and the use of all four tools is the most frequent choice (portfolio 16). In Hungary, the most frequent choice is combining contract farming with crop insurance (portfolio 8).

The empirical specification of the MESR is composed of three groups of explanatory variables ($\boldsymbol{X_i}$), reflecting the main elements of risk management adoption, namely farmers' risk behavior, allocation of resources and potential risks.

The first group consists of farmer characteristics (*age*, *gender*, *marital status* and *education*) and a binary variable whether the head of the farm does (=1) or does not (=0) work *off-farm*. In the literature, younger and more educated farmers often have higher adoption rates of risk management. This is linked with a better understanding and trust in insurance and contracts (Mishra and El-Osta 2002) and a greater ability to acquire and decode information for experimenting with new activities and/or varieties (Weiss and Briglauer 2000; Cole, Gine and Vickery 2013). *Off-farm* work is one form of household income diversification to reduce household income risks which is particularly common among smaller and family farms. Although the focus of our paper is on risk management practices for farm production, Weiss and Briglauer (2000) suggest that the exclusion of the off-farm employment status may introduce a bias in the parameter estimates, in particular of the farm size variable. Therefore, we decided to include this variable to avoid upward biases of the parameter estimate of farm size.

The second group of explanatory variables consists of farm characteristics. The four variables in this group are frequently considered in risk assessment. *Farm size* is negatively associated with production risks through greater capacity of smoothing shocks, thus reducing income variability (El Benni, Finger and Meuwissen 2016). On average, Hungarian farms are smaller than French farms, but with a relatively high standard deviation, meaning that very small farms coexist with very large farms. Insurers and contractors may give larger organizations quantity discounts because their losses are more predictable and because administrative costs decrease with size (Schmit and Roth 1990). From a production point of view, larger farms can benefit from economies of scale. A greater percentage of owned land reflects greater wealth, land control and access to credit, resulting in an overall stronger capacity of bearing risks and making productive investments, but also in a smaller need for risk management (Sherrick et al. 2004; Velandia et al. 2009; de Mey et al. 2016). Therefore, we expect that *land tenure* is positively related to productivity but negatively related to risk management adoption. *Subsidies*, especially direct payments, can increase farmers' wealth, lowering the level of risk aversion and therefore reducing farmers' adoption of risk management (Finger and Lehmann 2012). Moreover, subsidies can reduce the variance of income as much as business diversification, acting as substitutes for risk management tools (Spörri et al. 2012; van Asseldonk et al. 2016). As a consequence, wealthier farms with stable incomes are more likely to engage in productive investments (Vigani, Rodriguez-Cerezo and Gomez-Barbero 2015). Financial management can also play a critical role in risk management decisions and input choices, as highlighted by different authors (e.g. Sherrick et al. 2004; Chakir and Hardelin 2014; de Mey et al. 2016). Farmers with *liquidity* constraints are in greater need for external financing in case of crop losses and are more exposed to variations in the cost of credit, which increases risk aversion. Therefore, we expect a positive relationship between liquidity and adoption of risk management tools.

Note that the continuous variables *Farm size* and *Subsidies* were log-transformed. The regressors we use is a mix of binary, shares and continuous variables, therefore, by log-transforming the continuous variables, we obtain coefficients that are in level with the dependent variable.

The inclusion of a third group of variables (market risks) is motivated by the fact that, in contrast to well-diversified share-holder corporations in industrial sectors, agricultural companies face unsystematic and sector-specific market risks (Cornaggia 2013). Agricultural markets are inherently volatile because natural annual yield variations are combined with low and lagged price responsiveness of both supply and demand (Tangermann 2011). Moreover, government interventions are more frequent in the agricultural sector than in other sectors, and there are strong presumptions that agricultural policies add distortions to agricultural markets. For these reasons and following the example of other authors (Schmit and Roth 1990; Finger and Lehmann 2012), we include a binary variable based on farmer's self-assessment of *market shocks*, and the coefficient of variation of three years farm-gate wheat prices as a proxy for *price variability*.

So far we have assumed that farmers are risk averse; however, farmers may also have different preferences about risk, which can change the incentives for the adoption of risk management. Therefore, controlling for risk behavior is important. Behavior with respect to risk has two main components (Gardebroek 2006; van Winsen et al. 2014): i) risk perception (the farmer's subjective assessment of the likelihood that certain risks will occur and of the potential impact of those risks); and ii) risk attitude (the farmer's preference towards risks, from risk averse to risk seeking). Our dataset does not include a direct measure of risk attitude, but we are controlling for it indirectly.

First, we make use of the negative relationship between risk perception and risk attitude, i.e. the fact that risk averse (seeking) farmers tend to have higher (lower) subjective perceptions of risk (Cho and Lee 2006; van Winsen et al. 2014; Meraner and Finger 2017). We include an empirical measure of farmers' risk *perception* based on the following survey question: "Please assign the importance, from 1 to 5, to the following risk factors for your wheat production: hail, drought, flood and other natural disasters". Because natural hazards are geographically distributed (Vinet 2001), we assume that farms in the same region face similar natural risks, and that farmers may have different perceptions of potential damages provoked by effectively similar risks (i.e. a subjective perception of an objective risk). Therefore *perception* is equal to 1 if the farmer's assessment is higher than the regional mean; and 0 otherwise. In addition, we control for risk attitude also through several farm and farmer characteristics variables, especially age, education and farm size, which are well-known predictors for risk attitude (Dohmen et al. 2011; van Winsen et al. 2014). Age has a negative relation with risk taking or on risk attitude (Vroom and Pahl 1971; Moscardi and de Janvry 1977; Dohmen et al. 2011;). Higher education is proportional to risk taking behaviours (Moscardi and Janvry 1977; Harrison, Lau, and Rutström 2007; van Winsen et al. 2014). Farm size can affect risk attitude positively either direct (Feder 1980) or mediated via income (Fiegenbaum and Thomas 1988).

The specification of the selection equation (1) includes also the selection instrument *unions.* In the literature using MESR models to estimate the impact of farm practices and technology on productivity, the most common instruments used are those related to farmers' sources of information, such as farmers groups, cooperatives and extension services (Di Falco, Veronesi and Yesuf 2011; Di Falco and Veronesi 2013; Di Falco and Veronesi 2014; Kassie at al. 2015). However, such farmers groups and extension services might affect not only the adoption of risk management, but also productivity as they can be provider of inputs and technical support. On the contrary, *unions* are political organizations acting on behalf of farmers to obtain market protection, income support and stability, and public funding to compensate for natural disasters such as floods. In the EU, farmers' unions have a significant role in the formulation of the CAP and the Common Market Organization which provides all these forms of protection. Moreover, in many countries, including Hungary, *unions* organize mutual funds and insurances. In other words, unions deal with risk management at the policy level; therefore farmers joining a union are more likely to be informed about risks and tools for their management. On the contrary, farmers' unions are not input or technology providers, nor do they bring other production innovations, hence they are unlikely to have important effects on farms productivity. Furthermore, in the model we control for factors such as age and education, which are the main drivers of adoption of productive investments, therefore these effects can be hardly captured by *unions*, reducing the potential bias of unobserved heterogeneity and omitted variables. Finally, the validity and relevance of the instrument *unions* has been tested and established through falsification, Durbin, Wu-Hausman and C Sargan tests (see supplementary appendix II online) (Magrini and Vigani, 2016). For these reasons we consider *unions* a valid instrument, correlated with the selection variable (adoption of risk management portfolios) but uncorrelated with TFP.

In order to control for unobservable differences in technological level and farming system arrangements between France and Hungary, we follow the approach suggested by Mundlak (1978), Wooldridge (2002) and Di Falco and Veronesi (2013) to make use of the panel nature of the data. In the outcome equations (5) the time varying variables *age*, *farm size*, *tenure* and *subsidies* are included as their three years average. Moreover, *country*year* effects are also included. The alternative of including standard fixed effects and λ_i to the second step (where variables are transformed in deviations from their means) is particularly complex in MESR models and would not lead to consistent estimates (Wooldridge 2002; Di Falco and Veronesi 2013).

Finally, because of a large number of missing values in the variable *labor* (244 missing observations) used for the estimation of the TFP and in *subsidies* (422 missing observations), data imputation is used to improve the number of observations and retain the full sample of farms. The imputation technique used was the Gaussian normal regression imputation method, which is one of the most common methods for imputing quantitative continuous variables. The variables were log-transformed and regressed on a set of covariates. Because *labor* is a production factor, the covariates chosen were the ones commonly used to estimate production factors, namely wheat quantity, farm size, capital and intermediate inputs, doing imputations for each country separately. The covariates used to impute subsidies took into account that CAP payments are calculated based on productivity and location, therefore we used wheat yields and farm size, doing imputations for each region separately.

Results of the Multinomial Logit model

Table 3 shows the results of the multinomial logit model with sixteen risk management portfolios, derived from the combination of the risk management tools insurance, diversification, use of multiple wheat varieties and production contracts. Risk management portfolio 1 "No risk management" is the baseline category.

The relative probability of adopting risk management portfolios V (variety) and DV (diversification and variety) is significantly negative for farmer's characteristics *gender* and *married*, suggesting that married male farmers are less likely to adopt these portfolios. Older farms are less likely to adopt portfolios D, IC and IDV.

In our sample, the farmers working *off-farm* are more likely to adopt production contracts (portfolios C and IC) rather than diversification (portfolios D, DV and IDV). This is not surprising. According to Mishra and El-Osta (2002) farmers working *off-farm* have less time for self-protection from risks. Therefore, given that in order to engage in diversified activities the farmer needs to be trained and more informed to manage different types of productions, off-farm work reduces the farmers' time for training and gathering information.

Farm size is a significant driver of risk management portfolio adoption. The relative probability of adoption increases with farm size for the majority of the portfolios, with the exception of portfolio DC (diversification and contract, DC). Indeed, larger farms are more likely to have more managerial resources to devote to risk management, as well as the increasing returns to scale can help reducing the marginal cost of risk management (Weiss and Briglauer 2000).

In contrast, a higher proportion of owned land reduces the relative probability of adopting eight out of fifteen risk management portfolios, as the negative and significant coefficients of *Land tenure* show. This result is interesting and links to the work of Mishra and El-Osta (2002), Velandia et al. (2009) and Meraner and Finger (2017), showing that a higher proportion of rented land is associated to higher risk exposure and lower wealth. In other words, owned land can be seen as a collateral providing long-term rents and stability, therefore reducing the risk aversion of farmers.

Higher *subsidies* are associated with positive and significant probabilities of adopting portfolios D, ID, DV, DC and IDC, all of which contain diversification. In this respect, it is important to note that the greening component of the CAP is designed to increase agricultural diversification. However, higher subsidies reduce the relative probability of adopting insurance (portfolio I), probably reflecting the wealth effect described by Finger and Lehmann (2012).

A higher *perception* of risks is a positive driver of adopting insurance and insurance combined with multiple varieties (portfolios I and IV) but a negative driver of portfolios D, V, IC, DC and IDC. This suggests that the farmers with the highest perception of risks are likely to adopt the most direct types of risk management tools against risks of crop failure, such as crop insurance and variety diversification.

Farmers who have experienced *market shocks* are more likely to adopt a risk management portfolio (see portfolios I, ID, DV, IDV, ICV, DCV AND IDCV), suggesting that insurance or a bundle of tools are effective tools against market risks. The relative probability of adopting diversification and portfolios ID, DC, DCV and IDCV is significantly negative in case of *price variability*.

Results of the treatment effects

Figures 1, 2, 3, 4 and 5 show the difference in TFP between actual and counterfactual conditions of adopting different risk management portfolios obtained from the estimation of equation (7).

Across all figures, the adoption of risk management, when significant, has a negative impact on TFP, with a few exceptions. Remarkably, risk management portfolio IDV (insurance, diversification and variety) has always a negative and significant impact of at least - -38%, respectively. Portfolio DV (diversification and variety) also has a significantly negative impact on productivity of at least -11% very frequently, with the exclusion of French farms. The fact that many of the risk management portfolios show a significant TFP impact under various types of farming systems (France vs. Hungary) and levels of risks leads us to accept *H1*.

As expected, the largest losses of TFP occur with the most complex portfolios, IDV and IDCV, which consist of at least three different risk management tools. The exceptions are portfolio IV in Hungary (figure 3) and high risk farms (figure 4). As explained in the theoretical background, risk management tools require financial or management resources subtracted from the productive activity, - i.e. risk management comes at a cost. The fact that the losses of TFP are higher when additional risk management tools are adopted simultaneously is in line with *H2*. Therefore, additional tools and more complex risk management portfolios pile-up costs and management efforts, negatively impacting TFP.

Among the risk management tools adopted in isolation (portfolios I, D, V and C), insurance has a negative and significant impact of about -15/-18% in the full sample, Hungary and high risk farms. Multiple varieties (portfolio V) is significant only in low risk farms with a positive impact of +19% suggesting that, in productivity terms, "natural insurance" is a viable and efficient risk management tool in low risk conditions.

Interestingly, contracts (portfolio C) have a positive and significant TFP impact in almost all sub-samples, with the exception of France. The positive impact of contracts can be due to the financial and technical services, assets and technologies, which are often included in the agreements and provided by the buyers as a guarantee to acquire products with certain quality specifications and standards (Sexton 2012), or rolling contracts that provide longer term stability. It is also worth noting that the TFP impact of portfolios combining insurance with contracts (portfolios IC, IDC and ICV) is not significant, suggesting that the two might compensate and have a null TFP effect.

Additional important differences between French and Hungarian farms should be noted. In France (figure 2), only three out of fifteen risk management portfolios are statistically significant, all of them showing a negative TFP impact. In Hungary (figure 3), the statistically significant portfolios are seven, two of which with a positive TFP impact.

Almost all French wheat farmers in the sample have crop insurance, but it is usually used in combination with other risk management tools and rarely as a single risk management portfolio.

In France, the insurance system classifies risks into two categories: insurable (covered by the private market with limited government intervention) and uninsurable (covered by a public guarantee fund) (Chakir and Hardelin 2014). Among the uninsurable risks, drought and frost are the main ones which have become a source of major concern for wheat farmers in recent years (Vigani, Rodriguez-Cerezo and Gomez-Barbero 2015). In contrast, in Hungary the level of insurance adoption is quite low, which is also related to unsuitable and often unaffordable insurance products offered by private insurance companies (Spörri et al. 2012). In France, portfolio IDCV, which comprises all the risk management tools adopted simultaneously, have a large negative effect (-50%) that is highly statistically significant (in line with *H2*), but in Hungary the effect is not statistically significant. In Hungary, portfolio DCV has a positive and statistically significant TFP effect of +25%.

Comparing figures 4 and 5, seven risk management portfolios are significant in the sub-sample of high risk farms and only contract (C) has a positive TFP impact. A larger loss of TFP occurs with insurance and variety (portfolio IV). Cultivating varieties with different quality or resistance levels can increase costs associated with the diversification of agricultural practices and segregation, as well as searching for suitable markets (Vigani, Rodriguez-Cerezo and Gomez-Barbero 2015). Given the highest probability of crop failure under high risk conditions, it is possible that farmers devote more resources to manage risks than farmers in low risk conditions. In the sub-sample of low risk farms, six risk management portfolios have a significant impact and along with contracts, diversification and multiple varieties also has a positive impact. This suggests that in low risk conditions, the most efficient risk management portfolios are those with single tools, which are the less complex and do not accumulate costs of multiple strategies.

In order to gain a better understanding of the different impacts of risk management for different levels of risks (*H3*), we calculate the first difference between risk management portfolios of adopters and their counterfactuals (i.e. adopters if they did not adopt) in high and low risk conditions (Table 4).

In the third column of table 4 we calculate the difference between high and low risk adopters ((a)*hr* - (a)*lr)*. A statistically significant difference is observed for portfolios V, IV, DV, IDC and ICV. While for the first three significant portfolios the difference in TFP is negative, meaning that on average the TFP of low risk farms is larger, the difference turns positive for the adopters of portfolios 13 and 14, which combines three risk management tools instead of two. This suggests that, in line with *H3*, when risk conditions are harsher, more complex risk management portfolios are needed, otherwise any other "lighter" risk management strategy is not worth the effort (in productivity terms).

The difference between high and low risk non-adopters at the bottom of table 4 ((b)*hr* - (b)*lr)* is not statistically significant.

The fourth column of table 4 shows the difference between high and low risk counterfactuals ((c)*hr* - (c)*lr)*. For one portfolio (DV) the difference in TFP between high and low risk adopters and counterfactuals is confirmed. However, if high risk adopters decided to abandon portfolios D and IC they would achieve productivity gains, while if they decided to abandon portfolio DV they would achieve lower TFP losses. This suggests that the productivity impact of risk management is stronger in high risk conditions, consistent with *H3*.

Finally, in column four of table 4 we have calculated the second difference between treated high and low-risk farms (*TThr* – *TTlr*). The negative and significant differences of six portfolios show that larger changes in productivity occur more frequently in low risk conditions. This means that the losses in productivity due to the adoption of the six risk management portfolios are larger in high risk conditions rather than in low ones. This result suggests that we can accept *H3*. On the contrary, the positive and significant sign on portfolios ID, DC, IDV and IDC indicate that, for these portfolios, the losses of TFP, on average, are larger for low risk farms.

Discussion and conclusion

Risk management can be an important tool for stabilizing farm income during times of natural and market uncertainties, but it can also represent a net cost to farms, subtracting resources from agricultural production and therefore affecting productivity. Farmers need to take informed decisions about the most appropriate risk management strategies to adopt, tailored to their farming system and the probability of risks.

In this article, we addressed this issue by estimating the impact of the adoption of several portfolios of risk management strategies in different farming systems, and under different levels of risk. We focus on the case of wheat, as it is a risky staple crop highly concentrated in the EU with volatile yields and prices. We used survey data from a large sample of farmers in France and Hungary, estimating the impact of risk management on farm productivity with a multinomial endogenous switching regression model. This empirical strategy allows controlling for endogeneity bias and unobserved heterogeneity, and represents an improvement over previous studies by estimating a measure of total factor productivity (instead partial productivity) and accounting for unobservable production costs. It should be noted, however, that our model relies on strong exclusion restrictions, therefore our results should be interpreted as correlations rather than causal effects.

Our results show that productivity impacts vary according to the structure of wheat farming (which affects farmers' decisions regarding the allocation of production factors), and between different levels of risks (which affects the compensations resulting from risk management and the utility of income stabilization tools).

We show that risk management has a significant impact on farms' productivity, and that different risk management strategies have different impacts on TFP. In several situations, adopters of risk management portfolios are less productive than in the counterfactual case of non-adoption. This is for example the case for crop insurance adopters in France and diversification on high-risk farms. Production contracts have a positive impact on farm productivity in the majority of conditions, with the exception of France.

As hypothesized, because risk management is associated with a reallocation of resources towards the most risky production activities and, because of the direct costs of risk management, more complex risk management portfolios with simultaneous adoption of a combination of risk management tools have larger negative productivity impacts than simpler ones. Moreover, when farms operate with higher probability of risk, the use of complex risk management portfolios is more frequent, hence the impact on productivity is larger.

Even though in some circumstances risk management can result in lower productivity, this should not be interpreted as a reason for farmers to not manage risks. Both high and low risk farms cannot know at the beginning of the production season whether negative shocks will occur. For example, outbreaks of new pests or diseases can arise also in low risk areas. Therefore, a lower productivity can be considered part of the cost farmers have to pay in order to protect themselves against risks. Estimations of the impact of previous CAP reforms have shown a negative effect on farm productivity (see Vigani, Rodríguez-Cerezo and Gómez-Barbero 2015 for a review). In the light of our results, it should be noted that incentivizing risk management can have at least two potential consequences. On the one hand, providing farmers with cheaper risk management can reduce their direct costs, reducing in turn the negative productivity impact of risk management portfolios. However, promoting risk management without a serious justification linked to the probability of risk can provoke distortions in the allocation of resources and potentially reduce productivity. This has already been extensively discussed regarding subsidized insurance in the US (Goodwin 2001; Goodwin et al. 2004; Glauber 2004; Claassen, Langpap and Wu 2017; Du, Feng and Hennessy. 2017).

Given the significance of our results, further research on the potential effects of risk management should be encouraged. In particular, further applications to different agricultural products, as well as further applications to more countries with different production systems, would allow deeper understanding of the effects of risk management on the agricultural sector.

Finally, modern approaches based on cumulative prospect theory can provide further insights into the farmer's decision making process under risk, taking into account probability distortion and loss aversion, which we could only proxy with an indirect measure of risk attitude.

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Footnotes

[1] The model allows also calculating the treatment on the untreated TU as the difference between (b) and (d). Unfortunately, in our sample there are not enough French farmers with j=1 (see Table 2) for such computation.

[2] Producers are rewarded with a competitive price A up to a certain volume of wheat delivered. Additional volumes of wheat are purchased by the contractor at a lower price B which sometimes is below the costs of production. In some cases, an even lower price C is also applied.

Table 1. Summary Statistics of Variables Used in the MESR Model

Name	Variable description	Total sample		France		Hungary	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Outcome							
TFP	Log of total factor productivity estimated via Levinson and Petrin (2003)	4.934	2.162	5.498	2.163	4.382	2.015
Farmer characteristics							
Age	Age of the head of the farm (years)	49.757	10.808	48.605	9.932	50.910	11.508
Gender	= 1 if the head of the farm is a male	0.919	0.274	0.954	0.209	0.883	0.322
Married	= 1 if the head of the farm is married	0.767	0.423	0.674	0.469	0.860	0.347
Education	= 1 if the head of the farm has a university degree	0.271	0.445	0.263	0.440	0.280	0.449
Off-farm	= 1 if the head works also off the farm	0.090	0.286	0.030	0.172	0.150	0.357
Perception	=1 if the farmer has a higher perception of weather impact on productivity than the regional average	0.597	0.491	0.621	0.485	0.572	0.495
Farm characteristics							
Farm size	Log of total utilized area (Ha)	4.449	1.261	4.949	0.552	3.949	1.542
Land tenure	Percentage of TUA owned by the head of the farm	0.490	0.376	0.326	0.318	0.654	0.358
Subsidies	Log of CAP payments per hectare of wheat (€/Ha)	6.472	0.879	6.763	0.701	6.182	0.941
Liquidity	= 1 if the farm has sufficient liquidity to face unexpected events	0.524	0.500	0.451	0.498	0.597	0.491
Market risks							
Market shocks	= 1 if a severe drop in prices or increase in inputs cost happened in the last 3 years	0.720	0.449	0.691	0.462	0.749	0.434
Price variability	Coefficient of variation of three years prices	0.129	0.099	0.122	0.102	0.136	0.096
Instruments							
Unions	= 1 if the head of the farm is a member of a farmers union	0.200	0.400	0.357	0.479	0.043	0.203
Mundlak's FE							
Average age	Three years average age of the head of the farm (years)	49.757	10.778	48.605	9.899	50.910	11.479
Average farm size	Three years average of log of total utilized area (Ha)	4.449	1.256	4.949	0.551	3.949	1.534
Average land tenure	Three years average percentage of TUA owned by the head of the farm	0.490	0.375	0.326	0.317	0.654	0.357
Average subsidies	Three years log of CAP payments per hectare of wheat (€/Ha)	6.472	0.797	6.763	0.628	6.182	0.841

Table 2. Risk management portfolios

Portfolio Number	Risk management	Portfolio ID	% of Adoption All	France	Hungary
1	No RM	0	6.6	0.4	2.0
2	Insurance	I	5.6	0.2	3.3
3	Diversification	D	10.5	2.6	1.9
4	Variety	V	5.1	5.1	2.5
5	Contract	C	1.4	0.0	2.9
6	Insurance + Diversification	I,D	6.5	0.9	11.0
7	Insurance + Variety	I,V	6.6	6.0	3.7
8	Insurance + Contract	I,C	1.9	0.1	18.4
9	Diversification + Variety	D,V	11.8	18.2	5.1
10	Diversification + Contract	D,C	2.4	1.5	12.2
11	Contract + Variety	C,V	4.3	6.3	1.6
12	Insurance + Diversification + Variety	I,D,V	12.7	17.6	2.3
13	Insurance + Diversification + Contract	I,D,C	1.3	0.8	5.4
14	Insurance + Contract + Variety	I,C,V	3.8	6.0	7.7
15	Diversification + Contract + Variety	D,C,V	8.3	14.6	7.1
16	Insurance + Diversification + Contract + Variety	I,D,C,V	11.2	19.9	12.9
Total			100	100	100

Notes: Sample size = 2,100.

Table 3. Parameters estimates of risk management portfolios adoption, multinomial logit model

	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	I	D	V	C	I,D	I,V	I,C	D,V	D,C	C,V	I,D,V	I,D,C	I,C,V	D,C,V	I,D,C,V
Age	-0.010	-0.027***	-0.015	0.015	-0.012	-0.017	-0.061***	-0.012	-0.022	-0.012	-0.027**	-0.027	-0.014	0.000	-0.002
	(0.012)	(0.010)	(0.013)	(0.021)	(0.012)	(0.013)	(0.020)	(0.011)	(0.016)	(0.014)	(0.012)	(0.022)	(0.015)	(0.013)	(0.012)
Gender	0.163	-0.007	-0.865*	-0.129	-0.852**	-0.327	0.422	-0.899**	0.576	16.931	-0.918**	-1.620**	-0.568	-0.109	1.313*
	(0.490)	(0.389)	(0.443)	(0.668)	(0.405)	(0.487)	(0.824)	(0.416)	(0.643)	(2099.825)	(0.449)	(0.643)	(0.537)	(0.509)	(0.699)
Married	-0.933**	-0.422	-1.428***	-0.307	0.154	-0.227	-0.141	-0.750**	-1.089**	-0.414	-0.213	16.443	-0.377	-1.314***	-0.379
	(0.399)	(0.376)	(0.395)	(0.829)	(0.429)	(0.412)	(0.635)	(0.370)	(0.469)	(0.429)	(0.380)	(1543.175)	(0.442)	(0.379)	(0.382)
Education	-0.107	-0.195	-0.118	-0.463	0.357	-0.204	-0.318	-0.138	-0.224	0.498	0.502*	-1.352*	0.027	0.229	0.236
	(0.330)	(0.301)	(0.349)	(0.575)	(0.309)	(0.334)	(0.460)	(0.305)	(0.446)	(0.346)	(0.299)	(0.721)	(0.377)	(0.320)	(0.307)
Off-farm	-0.296	-0.599*	-0.230	1.125**	-0.566	-0.396	1.731***	-1.513***	0.104	-0.126	-1.050**	-1.320	-0.625	-0.660	0.126
	(0.366)	(0.340)	(0.444)	(0.474)	(0.374)	(0.445)	(0.433)	(0.575)	(0.521)	(0.468)	(0.516)	(1.085)	(0.593)	(0.499)	(0.402)
Log of Farm size	0.581***	0.072	0.724***	0.130	0.634***	1.423***	0.433**	0.939***	-0.312*	0.486***	1.567***	1.034***	0.535***	0.705***	0.912***
	(0.120)	(0.105)	(0.139)	(0.202)	(0.119)	(0.142)	(0.191)	(0.126)	(0.162)	(0.152)	(0.132)	(0.238)	(0.170)	(0.146)	(0.137)
Land tenure	-0.085	0.424	-1.078**	1.259	0.314	-0.315	-0.574	-1.085***	-0.248	-1.199**	-1.412***	-1.958***	-1.519***	-1.337***	-1.769***
	(0.444)	(0.409)	(0.449)	(0.973)	(0.431)	(0.432)	(0.660)	(0.400)	(0.594)	(0.477)	(0.410)	(0.738)	(0.502)	(0.430)	(0.420)
Log of Subsidies	-0.320**	0.751***	-0.070	-0.105	0.331**	-0.219	0.249	0.473***	1.215***	-0.022	0.206	0.480*	-0.078	0.130	-0.055
	(0.149)	(0.142)	(0.166)	(0.268)	(0.154)	(0.152)	(0.241)	(0.150)	(0.200)	(0.178)	(0.149)	(0.260)	(0.192)	(0.167)	(0.153)
Liquidity	0.425	0.100	-0.445	-0.733	-0.095	0.140	-0.372	0.241	-0.039	-0.001	-0.531**	-0.474	0.016	-0.317	-0.157
	(0.274)	(0.239)	(0.281)	(0.454)	(0.259)	(0.273)	(0.390)	(0.246)	(0.358)	(0.295)	(0.252)	(0.455)	(0.308)	(0.264)	(0.252)
Perception	0.818***	-1.096***	-0.513*	-0.488	-0.298	0.887***	-0.774*	-0.231	-1.006***	0.077	-0.387	-1.630***	0.030	0.252	0.257
	(0.315)	(0.242)	(0.287)	(0.434)	(0.264)	(0.305)	(0.405)	(0.255)	(0.360)	(0.312)	(0.258)	(0.478)	(0.320)	(0.280)	(0.265)
Market shocks	0.988***	-0.383	0.186	0.367	0.936***	0.077	16.283	0.686**	0.164	0.431	0.673**	0.558	0.618*	0.922***	0.603**
	(0.320)	(0.247)	(0.299)	(0.469)	(0.299)	(0.282)	(813.489)	(0.267)	(0.387)	(0.320)	(0.271)	(0.507)	(0.341)	(0.294)	(0.273)
Price variability	0.924	-6.623***	0.612	0.454	-2.709*	0.591	-3.883	-0.061	-5.218*	0.080	-1.153	-2.507	-1.024	-2.620*	-5.157***
	(1.128)	(1.645)	(1.215)	(2.399)	(1.561)	(1.186)	(3.009)	(1.126)	(2.842)	(1.347)	(1.281)	(2.684)	(1.602)	(1.498)	(1.550)
Unions	-0.384	-0.907*	-0.266	-14.216	0.001	-0.277	-14.845	0.029	-0.121	-0.102	-0.789*	-17.182	0.975**	0.282	0.478
	(0.552)	(0.533)	(0.489)	(1251.247)	(0.490)	(0.473)	(861.521)	(0.437)	(0.656)	(0.487)	(0.448)	(1695.986)	(0.474)	(0.446)	(0.436)
*Country*Year*	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-0.735	-1.457	1.035	-2.428	-3.508**	-3.868***	-16.301	-4.040***	-4.799***	-17.724	-4.287***	-19.865	-0.181	-1.852	-2.807*
	(1.341)	(1.207)	(1.444)	(2.351)	(1.387)	(1.471)	(813.491)	(1.350)	(1.826)	(2099.826)	(1.377)	(1543.177)	(1.684)	(1.488)	(1.480)

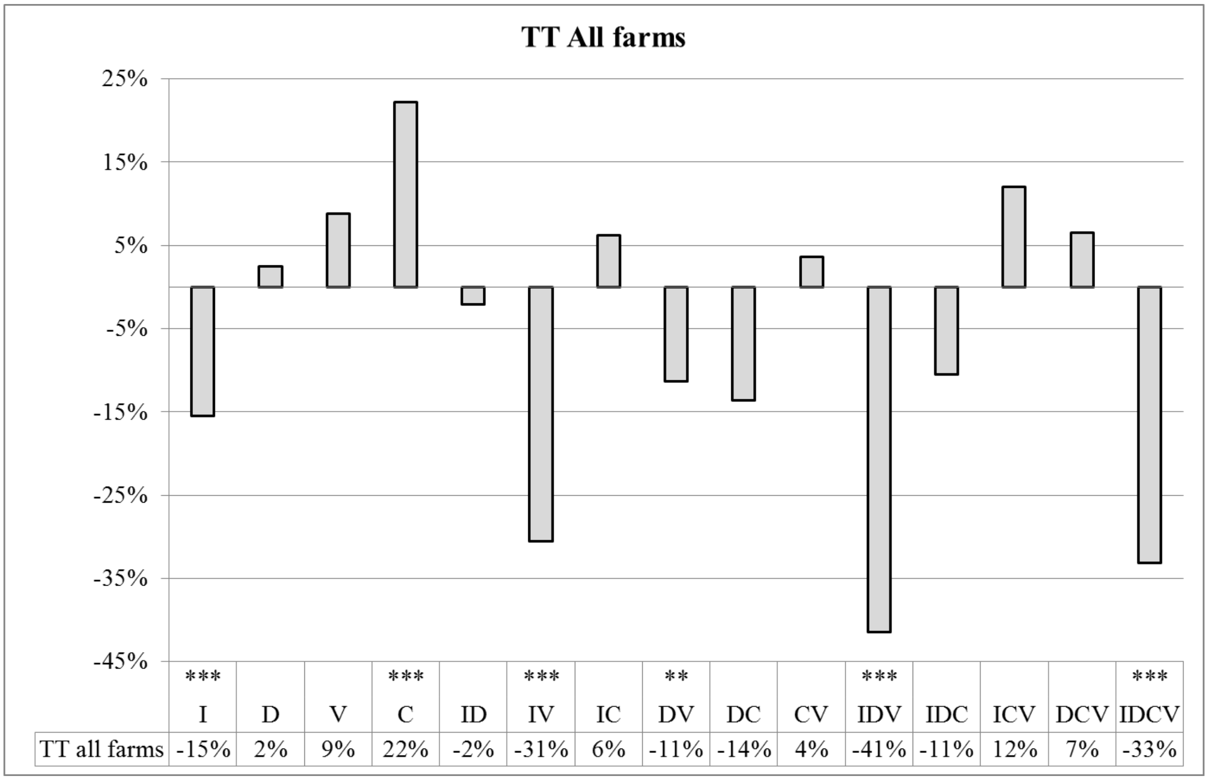
Notes: The baseline is portfolio 1=no risk management. Sample size = 2,100. Standard errors in parenthesis. Statistical significance at 1% (***), 5% (**) and 10% (*) levels.

Table 4. Results of the first and second difference between high and low risk farms

Portfolio Number	Portfolio ID	1st Diff. Adopters		1st Diff. Counterf.		2nd Diff. Treated	
		(a)hr - (a)lr		(c)hr - (c)lr		TThr - TTlr	
2	I	0.202		0.549		-0.347	***
3	D	-0.206		0.977	***	-1.182	***
4	V	-1.741	***	-0.493		-1.247	***
5	C	0.848		0.801		0.046	
6	I,D	0.250		-0.053		0.303	***
7	I,V	-0.875	**	0.625		-1.501	***
8	I,C	-1.116		0.968	**	-2.084	***
9	D,V	-1.113	***	-0.577	**	-0.536	***
10	D,C	0.641		-0.936		1.577	***
11	C,V	-0.190		-0.011		-0.179	
12	I,D,V	0.255		-0.021		0.275	***
13	I,D,C	1.207	**	-0.552		1.759	***
14	I,C,V	1.249	*	1.509		-0.260	
15	D,C,V	-0.035		-0.098		0.063	
16	I,D,C,V	-0.250		-0.137		-0.114	
1st Diff. NON Adopt.		(b)hr - (b)lr		-0.321			

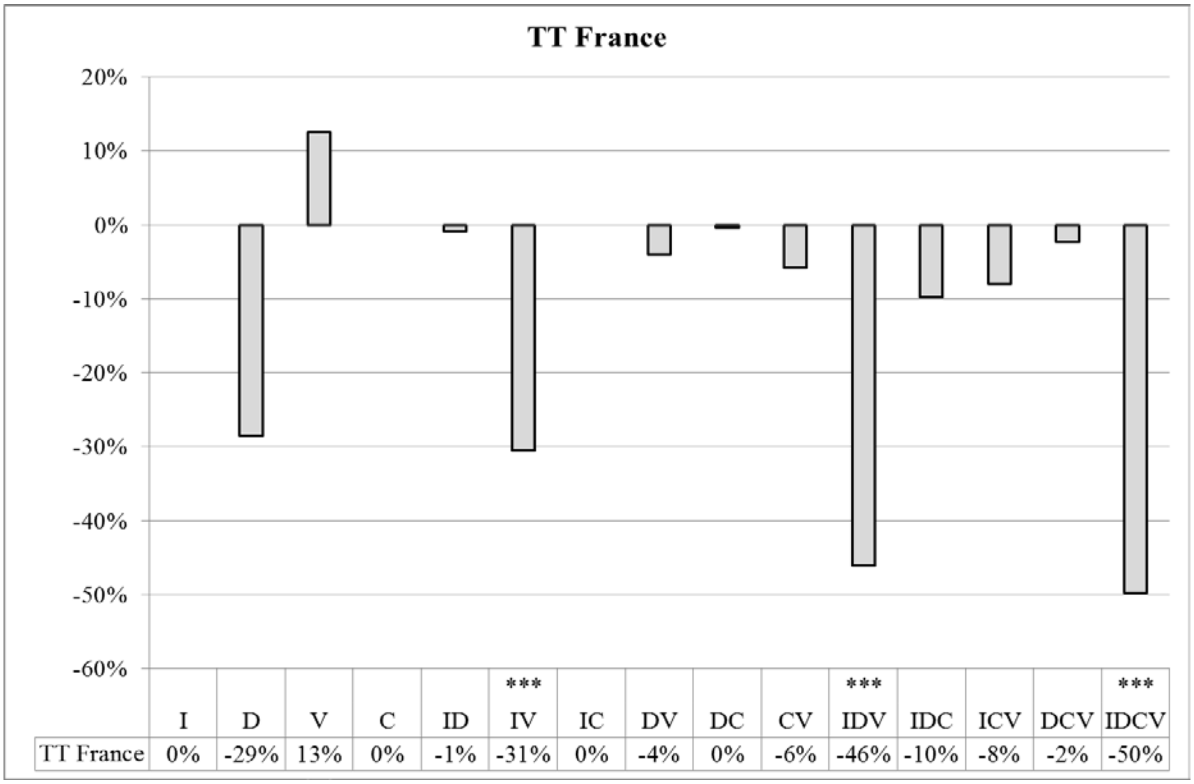
Notes: Statistical significance at 1% (***), 5% (**) and 10% (*) levels. Standard errors in parenthesis.

Figure 1. Treatment effect on the treated, all farms



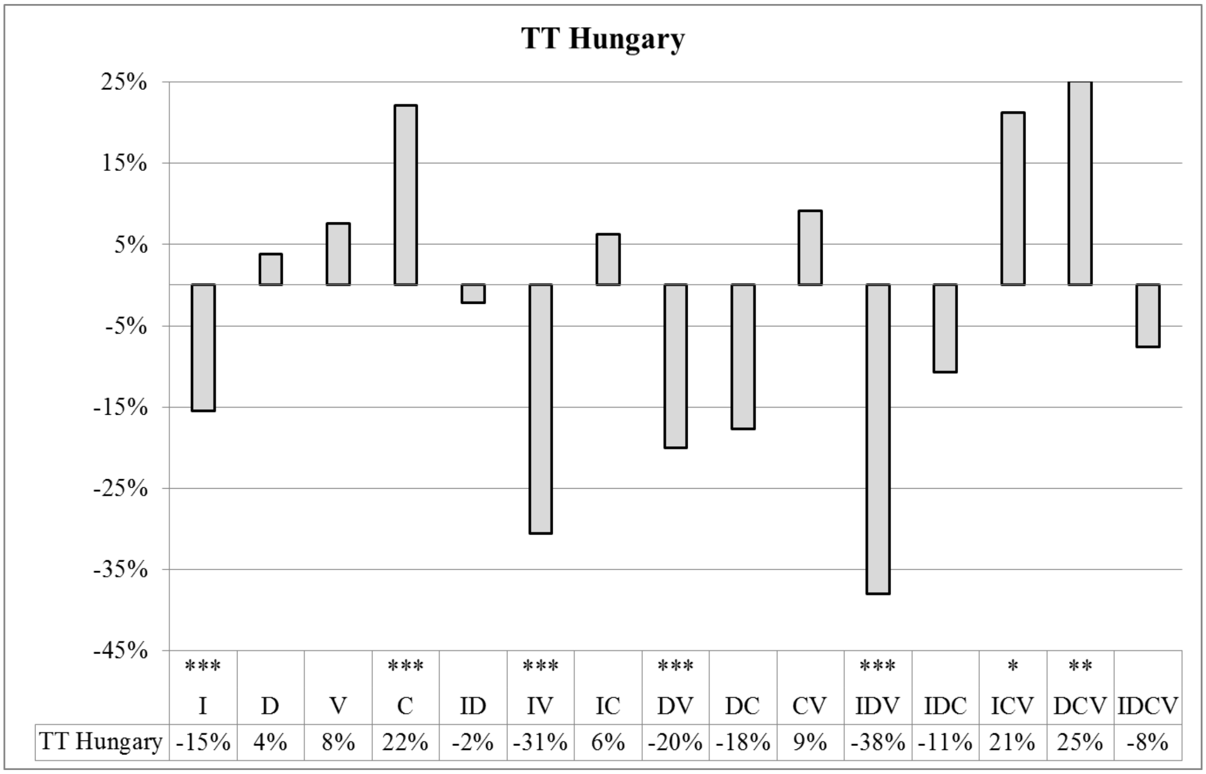
Notes: Statistical significance at 1% (***) and 5% (**) levels.

Figure 2. Treatment effect on the treated, France



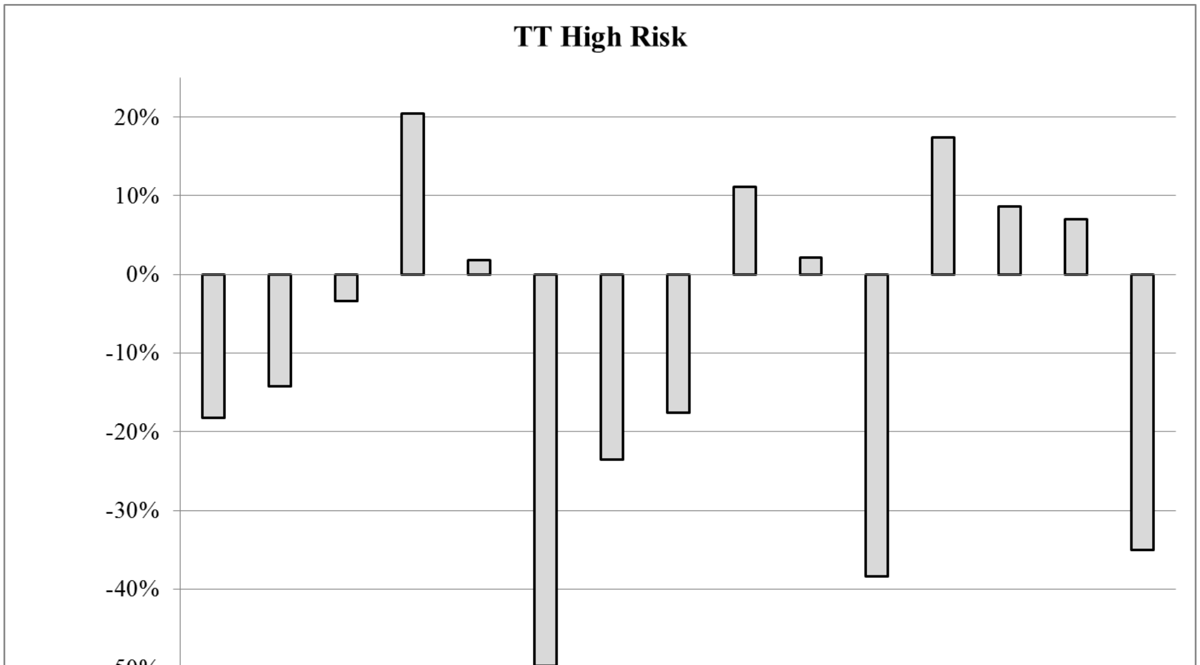
Notes: Statistical significance at 1% (***) level.

Figure 3. Treatment effect on the treated, Hungary



Notes: Statistical significance at 1% (***), 5% (**) and 10% (*) levels.

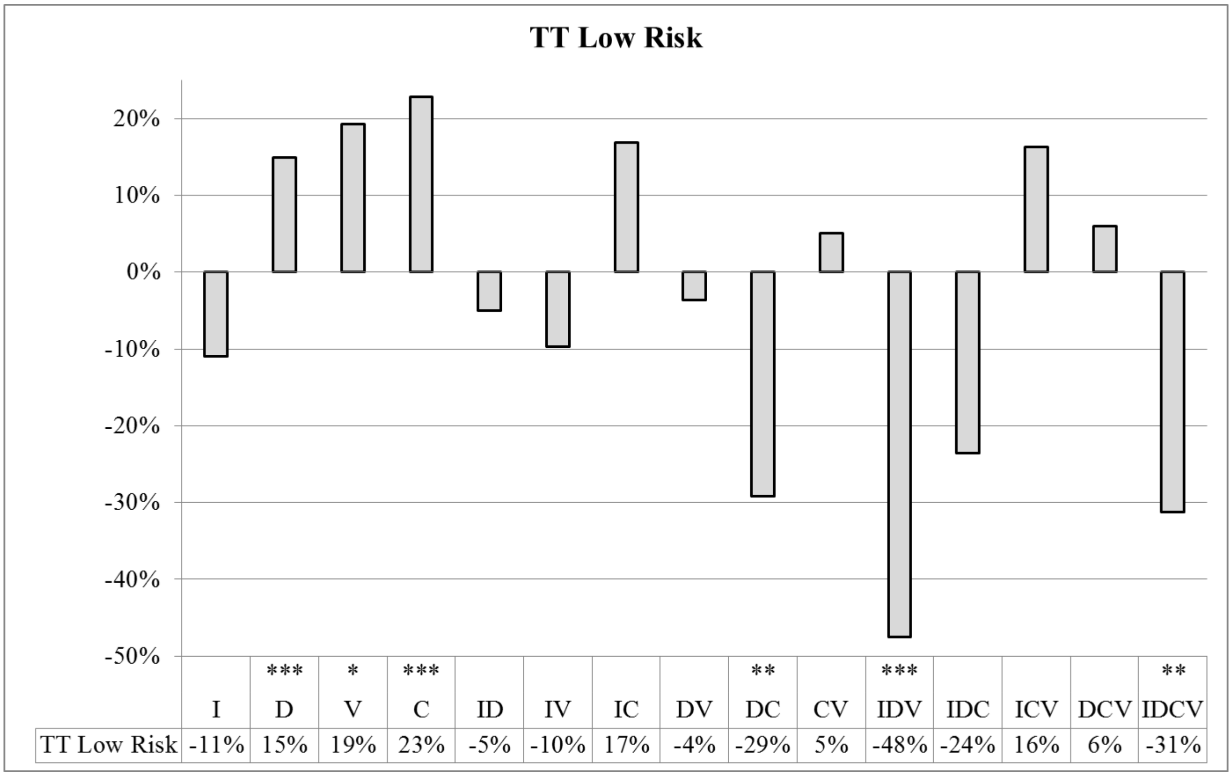
Figure 4. Treatment effect on the treated, high risk farms



	*** I	** D	V	*** C	ID	*** IV	IC	** DV	DC	CV	*** IDV	IDC	ICV	DCV	*** IDCV
TT High Risk	-18%	-14%	-3%	20%	2%	-50%	-24%	-18%	11%	2%	-38%	17%	9%	7%	-35%

Notes: Statistical significance at 1% (***) and 5% (**) levels.

Figure 5. Treatment effect on the treated, low risk farms



Notes: Statistical significance at 1% (***), 5% (**) and 10% (*) levels.