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"How laboratory experiments could help disentangle the influences of production risk and risk preferences on input decisions"

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How laboratory experiments could help disentangle the influences of production risk and risk preferences on input decisions

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Abstract: The purpose of this article is to further our understanding of input choices (such as pesticides or fertilisers) when producers face production risk that depends on a random shock and on the quantity of input used. Using laboratory experiments, we study the role of risk preferences and public policies (here, a lump-sum subsidy and insurance) on producers' input decisions in two situations: i) a risk-decreasing input; and ii) a risk-increasing input. Our findings raise questions on the sensitivity of optimal input choices to risk preferences and the relevance of the expected utility model to describe farmers' decisions.

Key words: laboratory experiment, input choice, production risk, risk preferences, subsidy, insurance.

1. Introduction

Farmers' production decisions often involve significant uncertainty. In this article, we focus on production risk and we study producers' decisions in terms of input use when the input either increases or decreases risk. Fertilisers and pesticides are typical examples of inputs that are known to impact not only the mean but also the variance of yields (Just and Pope, 1979). Since the use of such inputs may induce negative externalities and damage the environment, public intervention is justified. Having a good understanding of how farmers make their input decisions in a context of uncertainty is thus a prerequisite for an optimal design of agricultural and environmental policies.

There is a vast literature on the question of agricultural input use in a context of uncertainty. The empirical literature includes both reduced-form and structural input demand models which are estimated using either observational data (i.e., survey data) or experimental data, or both. Recently there was some controversy regarding the best strategy to identify technology parameters in the presence of production risk together with parameters of producers' risk preferences (Lence, 2009; Just and Just, 2011). The identification strategy based on the estimation of fully structural models (combining technology and risk preference equations) and using observational data only (e.g., Love and Buccola, 1991; Chavas and Holt, 1996) has been called into question. In response to this criticism, several authors relied on experimental approaches using framed field experiments run on a population of farmers. Some elicited risk preferences through lottery experiments and used the obtained risk preference measures as explanatory factors in (reduced-form) input demand equations estimated using observed data on input use (e.g., Liu and Huang, 2013; Le Cotty et al., 2017). Others relied entirely on data obtained from framed field experiments to assess both farmers' risk preferences and input use (e.g., Hill and Viceisza, 2012). This article adds to the recent literature by showing how laboratory experiments can help disentangle the impacts of risk preferences and production risk on input choices.[1] Through our experiments we are also able to test theoretical predictions about the impact (on input use) of risk preferences and public policies (a lump-sum subsidy and insurance) in a context of production risk. Hypotheses are derived under the assumption that producers' behaviour is

[1] See also Bellemare and Lee (2016) for a discussion of the usefulness of experimental economics to study the decisions of economic agents in the presence of price risk.

consistent with the expected utility theory. Even if recently challenged, the expected utility model has been used to a large extent to describe farmers' production under uncertainty.

In this article we frame the experimental task within a (general) production setting but the experiment has been designed to be highly relevant in an agricultural context. We specify a production function that is similar to those used in the agricultural economics literature and we set parameters for the technology that are in the range of those estimated from observed farm data. The output is produced from one major input but part of this output is uncertain. Production risk depends on a random shock over which subjects have no control, and on the quantity of input used. Subjects (who are not farmers) are informed about whether the input increases or decreases the risk of production and about the probability distribution of the random shock. The production technology is shown to the subjects, who can visualise the impact of their input decisions on both output and profit under different states of nature (which represent the uncertainty faced by producers at the time the decisions on inputs are made).[2] Based on this information on the technology and production risk together with information on the input and output prices, the subjects are asked to choose the level of input that maximises their profit. So, in the benchmark case, in which no public policy is put in place, input choices should be driven only by risk preferences. We then test how input choices change when two policies are implemented: first, a lump-sum and unconditional subsidy; and, second, a lump-sum and unconditional subsidy combined with mandatory insurance.[3] We define the technology as a Just-Pope production function that includes a risky component but, contrary to earlier studies using observational data, parameters are not estimated from the data but are chosen such that they are realistic in an agricultural context.

In Section 2 we provide an overview of the empirical literature which has studied the question of input choices in a context of uncertainty. The theoretical framework we build upon to derive major hypotheses to be tested in the laboratory is presented in Section 3.

[2] To our knowledge, in the experimental economics literature the production function has been shown to subjects only in public goods and common pool resource experiments. While observing production behaviour, industrial organisation experiments do not involve observed input choice with a production function shown to subjects but rather output choice given the output price and the production or cost function.

[3] With real data, insurance take-up is endogenous and selection bias must be taken into account. One nice feature of our experimental setting is that, by making the insurance mandatory, it becomes free from selection and endogeneity biases.

The experimental design is described in Section 4. Summary statistics and estimation results are shown and discussed in Section 5. Section 6 concludes.

2. Literature review: production risk, risk preferences, and input choices

We focus on empirical studies which aimed at achieving a better understanding of farmers' input choices. Since we are primarily interested in inputs that can be used by farmers to manage some risk of production in a context of uncertainty, we consider more specifically models that take production risk and risk preferences into account.[4] We discuss both structural and reduced-form models, primal and dual approaches, and studies relying on observational data and/or experimental data.

Earlier studies taking into account production risk and risk preferences primarily relied on observational data and estimated *separately* the parameters of the technology and risk functions. They used either programming approaches (e.g., Lin, Dean and Moore, 1974) or econometric approaches (e.g., Just, 1975), with risk preferences often characterised by a mean-variance utility function.[5] A few years later, Just and Pope (1978, 1979) emphasised the role of input choices on both mean yield and yield risk. They proposed specifying the production function as being made up of two components; one deterministic (to capture the effect of inputs on mean output), and one stochastic (to control for production risk through the effect of inputs on output variance). Since then, this specification has been used in many agricultural economics empirical applications to characterise production risk, i.e. how major agricultural inputs may increase or decrease yield variability.

Leathers and Quiggin (1991) used a Just-Pope production function and showed that a tax on pesticides, modelled as a risk-reducing input, has two effects on input use: a negative price effect but also a wealth effect that is negative for Increasing Absolute Risk Aversion (IARA) preferences and positive for Decreasing Absolute Risk Aversion (DARA) preferences. Isik (2002) extended the former model to incorporate output price risk. The impact of several

[4] We do not discuss in this review the link between risk preferences and technology adoption, in particular adoption of chemical inputs such as fertilisers by farmers in low-income countries. See for example Duflo, Kremer and Robinson (2011).

[5] The underlying idea of programming models was to find the risk aversion level that minimised the distance between observed input applications and optimal input rates.

policies is found to depend on the input being risk-reducing or risk-decreasing, on risk preferences, and on the strength of each risk.

The earlier approach based on a separate estimation of technology and risk preferences was criticised by some authors who argued that it does not properly account for production risk; that is, the effects of input choices on yield variability (Love and Buccola, 1991). Consequently, the *joint* estimation of a primal relationship (production technology) together with a function describing preferences was recommended in order to better account for the role of risk and risk aversion. Examples of such joint models include Saha, Shumway and Talpaz (1994), Chavas and Holt (1996), Kumbhakar and Tveteras (2003), and Koundouri et al. (2009). The function describing risk preferences can have various degrees of flexibility but, in general, the producer's behaviour is assumed to be consistent with expected utility theory and first-order conditions are derived from the maximisation of the expected utility of profit. The main outcomes of such models are estimates of risk preferences (risk aversion coefficient, relationship between risk aversion and wealth) and estimates of the technology (marginal effect of inputs on the mean and the variance of yield).

The assumption that deviations from profit-maximising behaviour are entirely driven by risk preferences, together with restrictions imposed on the form of the utility function and risk preferences and/or on the technology, has been considered quite strong by Lence (2009) and Just and Just (2011). These authors pointed out that wrong assumptions about the form of the utility function and/or the technology could cause severe estimation biases. Their work thus seriously called into question the validity of the strategy of joint estimation of risk preferences and production technology from revealed preference data, for separate identification of technology and risk parameters.

In response to these criticisms, some authors proposed to "go back" to a separate estimation of technology and risk parameters by eliciting, in the first stage, risk preferences from field experiments. Measures of risk preferences (such as the coefficient of risk aversion) are then used, in the second stage, as explanatory variables in (reduced-form) input demand equations estimated using observational (real) data. Elicitation of risk preferences followed various experimental protocols and some authors went beyond the (commonly used) expected utility theory by allowing for more flexible preferences such as those derived from prospect theory.[6] Among others, this two-stage approach was followed by Liu and Huang (2013), Gong et al. (2016) and Le Cotty et al. (2017). As indicated by some of these authors, estimates of the coefficients in the (second stage) input demand equation could be biased if unobserved farmers' characteristics explain both risk preferences and input use. In these articles the production technology and the impact of input use on production risk are not explicitly modelled.

Finally, another strand of the literature includes Hill and Viceisza (2012) and Saenger et al. (2013), who studied agricultural input choices in a risky setting by relying exclusively on experimental data that they gathered using framed field experiments.[7] The experimental protocols that have been designed thus go beyond "traditional" risk protocols involving (only) a choice over monetary lotteries. For example in Hill and Viceisza (2012), each farmer receives a random amount of money at the start of the game and can use this initial endowment to purchase zero, one, or two bags of fertiliser. The purchase decision is made without knowing future weather conditions (weather can be either good or bad). The quantity of input applied and the weather determine farmer's income. Farmers' input decisions are compared in two situations: i) a benchmark situation without any insurance; and ii) a situation with mandatory (actuarially fair) insurance. The experiment was run with 261 farmers from Ethiopia. Very similar to this was the experiment conducted by Saenger et al. (2013) with 185 dairy farmers from Vietnam. This studied the effectiveness of contracts between smallholders and milk processing companies to improve milk quality.[8]

Empirical applications are numerous and have used highly diverse data in terms of the countries and types of production covered. There is much heterogeneity in the conditions under which farmers operate (climate and weather, institutions, access to input and output markets etc.) so it is not surprising that the main conclusions on the impact of inputs on production risk and the relationship between risk preferences and input choices vary from one study to another.

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[6] See Bocquého, Jacquet and Reynaud (2014) and Bougherara et al. (2017) for elicitation (using field experiments) of French farmers' risk preferences under both expected utility and prospect theories.

[7] Framed experiments are characterised by "less abstract framing with choice tasks mimicking day-to-day decisions as well as more tangibly defined commodities" (Saenger et al., 2013).

[8] We do not discuss here studies that used framed experiments to assess farmers' adoption of innovations. One such example is Brick and Visser (2015) who studied, in the lab, the decision of 82 South African farmers to adopt high-yielding seeds, which required them to take out a loan. Since these innovative seeds may be more profitable but also more risky, farmers are then proposed a loan that is bundled with rainfall insurance.

Fertilisers are often considered as an example of inputs that increase output variance (Just and Pope, 1979) while pesticides are usually believed to decrease production risk. However, empirical evidence does not always confirm these beliefs. For example, Serra et al. (2006), in a study of 596 farms in Kansas, found both fertilisers and pesticides to be risk-increasing inputs. Di Falco and Chavas (2006), using data from durum wheat farms in Sicily (Italy), found no statistically significant effect of fertilisers on output variability while pesticides were found to reduce production risk. Gardebroek, Chavez and Oude Lansink (2010), using data from both organic and conventional farms in the Netherlands, found fertilisers to be risk-increasing inputs on organic farms and risk-reducing inputs on conventional farms. Koundouri et al. (2009), using a panel of Finnish crop farms, found both fertilisers and plant protection products to be risk-decreasing inputs. This discrepancy in findings regarding the effect of inputs on production risk may also be explained by the effect of inputs varying depending on whether crop growth conditions are good or bad (Horowitz and Lichtenberg, 1994).

Regarding the relationship between risk preferences and input levels, Liu and Huang (2013) found that Chinese cotton farmers who are more risk averse use greater quantities of pesticides and farmers who are more loss averse use lesser quantities of pesticides. Gong et al. (2016) found that risk aversion significantly increases pesticide use, but only for subsistence farmers (who produce only for home consumption), with a stronger effect on small farms. Le Cotty et al. (2017) found no statistically significant effect of risk aversion on fertiliser use by maize farmers from Burkina Faso. Hill and Viceisza (2012) found that mandatory insurance increased fertiliser purchase and the effect of the insurance was found to increase with the level of risk aversion. In Saenger et al. (2013) risk aversion was not found to significantly affect the purchase of inputs.

3. Theoretical framework

We describe in this section the farmer's optimisation programme under uncertainty and derive theoretical predictions in terms of input use in the two cases of a risk-increasing input and a risk-decreasing input. We derive testable hypotheses about the relationship between risk preferences and quantity of input use (Section 3.1.) as well as hypotheses on the impact of public policies on the level of input (Sections 3.2. and 3.3.). Throughout we assume that farmers face some production risk which itself depends on the quantity of input use and a random shock, and that farmers' behaviour is consistent with expected utility theory.[9]

3.1. Farmer's optimisation programme

We assume the simple case of a farmer producing one risky output z (sold at price p_z) with a single input x (purchased at price p_x). The production function is specified as follows:

$z = f(x) + g(x)\varepsilon$.

This is made up of two components: $f(x)$ is the mean production function; and $g(x)$ represents the variance or risky component of the production technology (Just and Pope, 1979). The random term ε is a shock that may affect output and is exogenous to the farmer's actions. We assume $E(\varepsilon) = 0$ and $V(\varepsilon) = \sigma^2$. This idiosyncratic random shock, which may be a weather shock or a pest attack affecting only yields but not prices, makes profit random. The risk function $g(x)$ captures the effect of input x on risk: if $\partial g/\partial x < 0$ then input x is said to be risk-decreasing while it is risk-increasing if $\partial g/\partial x > 0$.

We assume the farmer chooses the level of input x that maximises his/her expected utility of profit:

$$Max_x \; EU\left[\pi(x)\right] = EU\left[p_z z - p_x x\right] = EU\left[p_z\left(f(x) + g(x)\varepsilon\right) - p_x x\right]$$

where U is an increasing and continuously differentiable utility function.

We get the following first-order condition: $\frac{\partial f}{\partial x} = \frac{p_x}{p_z} - \frac{\partial g}{\partial x}\theta$, with $\theta = \frac{E\left[U'(\pi)\varepsilon\right]}{E\left[U'(\pi)\right]}$ and $U'(\pi)$ the marginal utility of profit. The function $\theta(.)$ represents the farmer's risk preference function and depends on the form of the utility function $U(.)$, farmers' input choice (x), input and output prices (p_x and p_z), and the random shock (ε).

If the farmer is risk-neutral then $\theta = 0$ and the first-order condition simplifies to: $\frac{\partial f}{\partial x} = \frac{p_x}{p_z}$. If the farmer is risk-averse then $\theta > 0$ and the optimal quantity of input x will be higher than

[9] Empirical structural models that have been estimated in the past and that are quoted in the literature review almost all rely on this theoretical setting.

in the risk-neutral case if x is risk decreasing $\left(\partial g/\partial x<0\right)$. On the other hand, the optimal quantity of input x will be lower than in the risk-neutral case if x is risk increasing $\left(\partial g/\partial x>0\right)$. If the farmer is risk-loving then $\theta<0$ and the farmer will use more of the risk-increasing input and less of the risk-decreasing input than in the risk-neutral case. In what follows we restrict the analysis to the case of risk-averse decision makers, which corresponds to the utility function U being concave ($U''(\pi)<0$).[10]

Our experiment allows the above theoretical predictions to be tested; that is, the relationship between risk preferences and input choices in a context that is free from any public policies. More precisely, we test the following two hypotheses:

H1-a: in the benchmark situation without any policy in place, risk-averse subjects choose a quantity of input x that is higher than the optimum for a risk-neutral agent if x is risk-decreasing, and lower than the optimum for a risk-neutral agent if x is risk-increasing.

H1-b: in the benchmark situation without any policy in place and for risk-averse subjects, the quantity of input x increases with the level of risk aversion if x is risk-decreasing, and decreases with the level of risk-aversion if x is risk increasing.

In what follows we discuss the introduction of two public policies: a lump-sum and unconditional subsidy (Section 3.2.) and a lump-sum and unconditional subsidy coupled with mandatory insurance (Section 3.3.).

3.2. Introduction of a lump-sum and unconditional subsidy

A lump-sum subsidy, unconditional and decoupled from production, makes farmers wealthier. This wealth effect will impact production choices except if farmers exhibit Constant Absolute Risk Aversion (CARA). A positive shock on wealth induced by a lump-sum subsidy will make producers with Decreasing Absolute Risk Aversion (DARA) less risk averse, but it will increase the risk aversion of producers characterised by Increasing Absolute Risk Aversion (IARA). As a consequence, a direct subsidy will not change the quantity of input use of CARA producers but it will encourage the use of a risk-increasing input and discourage the

[10] There exists empirical evidence that farmers are risk-averse and that their preferences are consistent with Decreasing Absolute Risk Aversion in most situations (see, for example, Table 1 in Just, 2011).

use of a risk-decreasing input for DARA producers. As for IARA farmers, a direct subsidy will increase their use of a risk-decreasing input and decrease their use of a risk-increasing input (Leathers and Quiggin, 1991). We have the following hypothesis:

H2: when offered a lump-sum and unconditional subsidy, risk-averse subjects will adjust the quantity of input x as long as their preferences are not CARA. For those who have DARA preferences, a lump-sum subsidy will increase their use of a risk-increasing input and decrease their use of a risk-decreasing input. For subjects with IARA preferences, a lump-sum subsidy will increase their use of a risk-decreasing input and decrease their use of a risk-increasing input.

3.3. Adding mandatory insurance

We consider a policy that combines the lump-sum and unconditional subsidy with mandatory insurance.[11] The insurance contract is defined through an indemnity and a premium and is assumed actuarially fair (i.e., the insurance premium equals the expected value of the loss). Insurance is made mandatory to avoid selection bias in the measurement of the insurance effect on input use. Insurance contracting has two effects on production choices (Ramaswami, 1993):

(i) a risk-reducing effect: the insurance reduces risk so the contracting of an actuarially-fair insurance will induce risk-averse farmers to increase input use if the input is risk increasing, and to decrease input use if the input is risk decreasing; and

(ii) a moral hazard effect: with insurance, a change in input use affects output and hence indemnities. The marginal return of input application is now computed as the marginal gain in production (the additional output that is produced from a marginal increase in input x) minus the resulting loss in indemnities. Since the marginal return of input use is lower than in the case without insurance, insurance will induce farmers to reduce input use, irrespective of whether the input is risk increasing or risk decreasing.

We have the following hypothesis:

H3: with a lump-sum subsidy and mandatory (actuarially-fair) insurance, and compared to the case of a lump-sum subsidy only, risk-averse subjects will choose a lower level of input

[11] There are two main reasons for considering a policy combining these two instruments. First, it is realistic in the sense that most farmers, especially in the European Union, receive subsidies. Second, considering the two instruments separately would have implied running a larger number of sessions in the laboratory.

x if the input is risk decreasing. In the case of a risk-increasing input, the total effect is ambiguous (since the risk effect tends to increase input use while the moral hazard effect tends to decrease input use).

4. Experimental design

The theoretical framework described in Section 3 involves two variables that are difficult to observe in the real world: individuals' risk preferences and production risk. Our experimental design thus seeks to control for these unobservables by eliciting risk preferences separately from input choices and by building a controlled risky environment (i.e., the random component is controlled by the experimenter and known by the subjects). Our design consists of two main parts. In the first part (risk elicitation task), subjects' risk preferences are elicited. The second part (production task) is a game where subjects play the role of producers and purchase an input in a controlled risky environment (see Appendix A for an example of experimental instructions). We ran the experiment on a sample of students rather than farmers since our aim was to test the theoretical predictions of a specific model. Also, we chose to de-contextualise the experiment to avoid choices being driven by attitudes or opinions towards the use of inputs such as fertilisers or pesticides in agriculture. Incentives and order effects are discussed in Appendix B.

4.1. Risk elicitation task

In order to elicit subjects' risk preferences, we use a series of binary lottery choices in a protocol similar to Holt and Laury (2002)'s multiple price list (see Appendix C). Subjects face a series of 11 lottery choices where a choice has to be made between lotteries A and B. Lottery B has more variable payoffs than lottery A. As one moves down each row, the expected value of lottery B exceeds, to a greater and greater degree, the expected value of lottery A. Row 1 and row 11 involve no risk and allow checking for behavioural consistency. We define a variable r capturing risk preferences equal to the row at which subjects switch from lottery A to lottery B: $r = 5$ for a risk-neutral subject; $r > 5$ for a risk-averse subject, and $r < 5$ for a risk-loving subject.

4.2. Production task

The objective is to test our theoretical predictions in terms of input use in relation to risk preferences and public policies. We control for risk by stylising it as rolling a dice with probabilities and events being common knowledge. Subjects make six input decisions (in six consecutive rounds) in a given treatment (treatments are described below). For each treatment, the production task comprises the following steps:

Step 1: At the beginning of the first round the subject is assigned an initial endowment $w = 1{,}500$ ECUs (Experimental Currency Unit).[12]

Step 2: The subject decides the quantity of input $x \in [0{,}600]$ to buy at a unit input price $p_x = 1$. Any unit of input purchased enters the production process and the quantity of output produced is fully determined by the random component ε and the amount of input applied (see Step 4).

Step 3: The random term ε is determined by rolling a dice to facilitate subjects' understanding of the risky component. We specify a symmetric risk with three states of nature (featuring bad, average and good production conditions) so that ε=[(-1,1⁄6);(0,4⁄6);(1,1⁄6)].[13] If the result of the dice is 1 (probability of occurrence equal to 1/6), then ε=-1, nature is in the "bad" state, the conditions are unfavourable for production and yields are low; if the result of the dice is 2, 3, 4 or 5 (probability of occurrence equal to 4/6), then ε=0 and yields are 'normal' (average conditions), and if the result is 6 (probability of occurrence equal to 1/6), then ε=1, production conditions are highly favourable (good state), and yields are high.

Step 4: The output level is determined by the subject's choice of input (Step 2) and the fall of the dice (Step 3) according to the following function: $z = [f(x) + g(x)\varepsilon]$. The specifications we used for functions f and g are described below. The subject receives an income according to the realised output level and the unit output price $p_z = 10$. This income is added to the initial endowment and is determined as follows:

$$w + p_z z - p_x x = 1500 + 10[f(x) + g(x)\varepsilon] - x.$$

[12] Profits are expressed in ECUs and the conversion rate in the production task is 1 Euro for 2,000 ECUs.

[13] The question of the normality of agricultural yields has been extensively discussed in the literature (see, e.g., Just and Weninger, 1999; Atwood, Shaik and Watts, 2003; and Claassen and Just, 2011). This is outside the scope of our study. For simplicity, we consider yields to be symmetric.

Step 5: Once the first round of the game is completed, Steps 1 to 4 are repeated five additional times, which amounts to a total of six rounds for each treatment.

We specify the following Just and Pope (1979)-type production functions:

$$z = \begin{cases} 20^{0.3} + x^{-0.1}.\varepsilon & \text{if the input is risk decreasing} \\ 20^{0.3} + x^{0.1}.\varepsilon & \text{if the input is risk increasing} \end{cases}$$

The chosen parameters for the elasticity of mean output (0.3) and the elasticity of output variance (+/- 0.1) to input application are in the range of estimates reported in the literature using data for crop farms. For example, Just and Pope (1979) estimated the elasticity of mean yield for corn and oats (measured in bushels per acre) to fertiliser application (in pounds of nitrogen per acre) and found values in the range 0.3-0.4. Elasticities of output variance were found to be statistically significant and around 0.1-0.2 for both crops.[14]

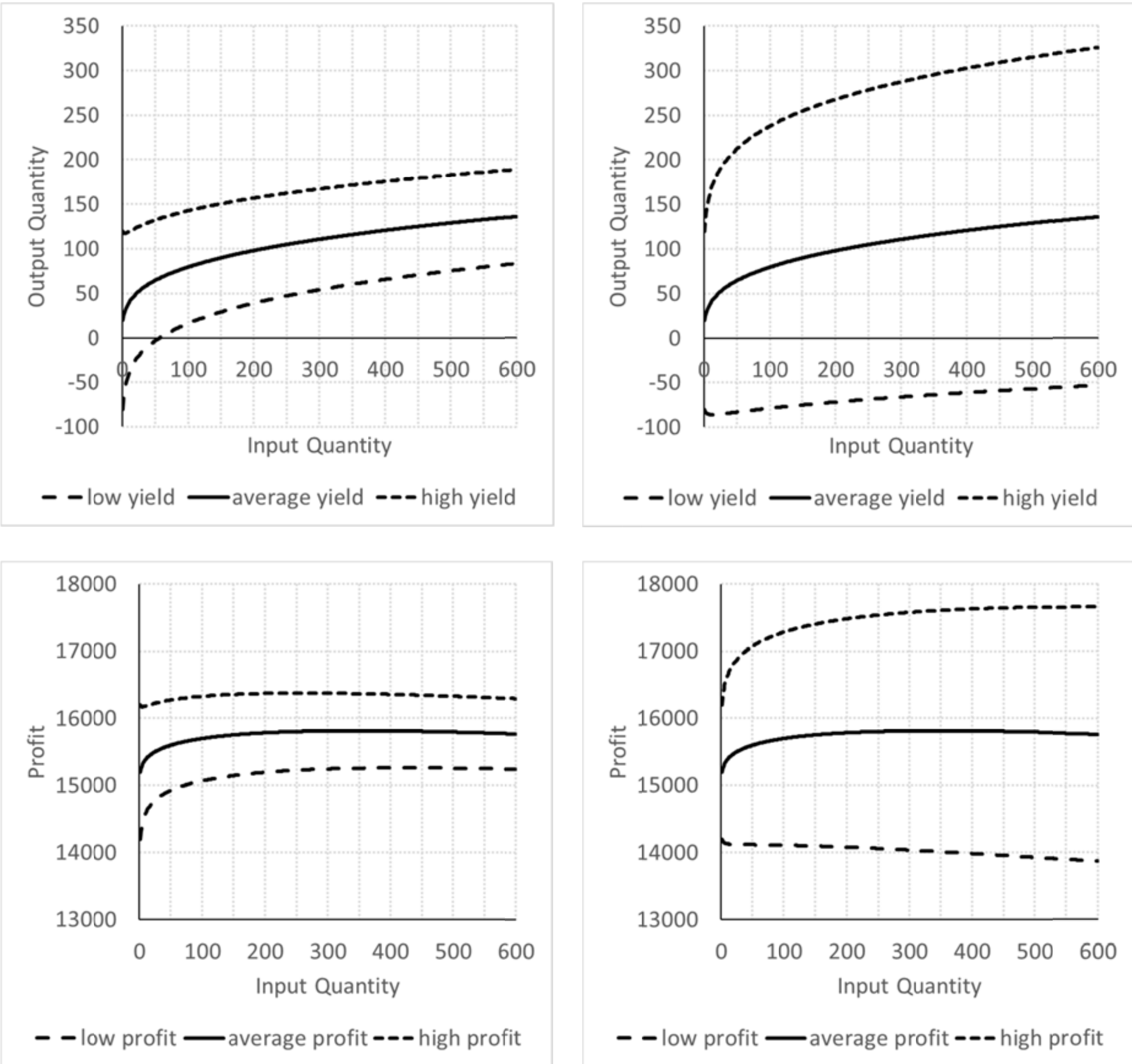
In Step 4, the output level is determined according to the subject's choice of input and the fall of the dice. Hence there are six production functions and six profit functions according to the type of input (two types) and the realisation of the risk (bad, average or good state).[15] The left panel of Figure 1 depicts the three production functions and the three profit functions for each value of the random variable ε in the risk-decreasing case. Production increases with increased levels of inputs but at a decreasing rate. The three curves converge because using more of the input decreases risk. The associated profit function is also displayed to subjects.[16] The right panel of Figure 1 shows the production and profit functions in the case of a risk-increasing input. The three curves diverge since input x is risk-

[14] In Gardebroek, Chavez and Oude Lansink (2010), using survey data for arable farms in the Netherlands over a 10-year period, the estimated elasticity of mean output to herbicides and pesticides (all measured with quantity indices) was 0.23 (for conventional farms). The elasticity of production risk (or output variance) was 0.21 but was not statistically significant. Some slightly higher elasticities of mean output were reported by Koundouri et al. (2009) in their study of Finnish crop farms: 0.50 for plant protection and 0.77 for fertilisers, but elasticities of output risk were in the low range: -0.02 for fertilisers and -0.05 for plant protection. Finally, in a study of the French farm data from the Meuse *département*, Femenia and Letort (2016) estimated the marginal productivity of both fertilisers and pesticides at around 0.1.

[15] The Just and Pope (1979)-type production functions that were chosen allowed for negative output. Since our experiment is context free, this is not an issue. The endowment at the beginning of each round ensured profits were never negative. Another option would have been to define production functions where output was always positive and to get rid of the endowment.

[16] Under a risk-neutrality assumption, the theoretical optimal input use is x^* = 261 in the good state of nature, x^* = 347 in the average state of nature, and x^* = 419 in the bad state of nature.

increasing.[17] To assist subjects in choosing the level of input, a scroll bar (representing various levels of inputs) could be moved along the horizontal axis of each graph. Subjects could play with the scrollable cursor and could directly observe, on the screen, how changing input use affects output levels and associated profits (see Appendix A). Their final input choice had to be validated by clicking on a specific key.



(a) risk-decreasing input

(b) risk-increasing input

Figure 1. Production and profit functions under the three states of nature (bad, average and good), for a risk-decreasing input (left panel) and for a risk-increasing input (right panel)

[17] Under a risk-neutrality assumption, the theoretical optimal input use is x^* = 1 in the good state of nature, x^* = 347 in the average state of nature, and x^* = 598 in the bad state of nature.

The production functions and the profit functions in Figure 1 all have a relatively wide plateau. This is a rather common feature of models of production response to inputs and payoff functions in agriculture (Pannell, 2006). In such cases, large deviations from the optimum (in terms of input use) may induce limited variation in the expected payoff.

4.3. Description of the treatments

We consider three treatments: i) *BENCH*, the benchmark or no-policy treatment; ii) *SUB*, a treatment in which a lump-sum and unconditional subsidy is offered to the subjects; and iii) *SUB&INS*, a treatment in which the lump-sum subsidy is coupled with mandatory (actuarially-fair) insurance. We use a within-subject design for the policy treatments, which allows for full control of unobservable individual variables, and we use a between-subject design for the input type (implying that each subject is exposed to one type of input only); cf. Table 1.

Table 1. The three treatments in the production task

Type of input	Treatments		
Risk-decreasing input	*BENCH* (6 rounds)	*SUB* (6 rounds)	*SUB&INS* (6 rounds)
Risk-increasing input	*BENCH* (6 rounds)	*SUB* (6 rounds)	*SUB&INS* (6 rounds)

We define a stylised subsidy and a stylised insurance policy with the objective of mimicking the situation in countries of the European Union (EU). The subsidy is set at 300 ECUs, which roughly corresponds to 30% of production value.[18] Given the specification we chose for production functions, optimal input use is 347 under the average yield condition ($\varepsilon = 0$), which corresponds to an optimal output of around 100 units. At unit price $p_z = 10$ ECUs, production value thus reaches around 1,000 ECUs and a 30% subsidy corresponds to 300 ECUs.

[18] We chose 30% based on statistics provided by the European Commission and indicating that "the EU average share of direct payments in agricultural income in 2011-2015 stood at 28%." (European Commission, Graph 5 available at https://ec.europa.eu/agriculture/graphs-figures/cap_en; accessed 3 February 2018).

The mandatory insurance is such that subjects have to pay a cost $m_{RD} = 8$ output units[19] whatever the state of nature and an indemnity $I_{RD} = 48$ output units which is paid only in the case of an unfavourable fall of the dice ($\varepsilon = -1$ with probability $1/6$).[20] Insurance is always actuarially fair such that the expected benefit of insurance is equal to the cost: $m = \frac{1}{6} \times I$. For simplicity and to avoid incorporating additional sources of variation in the design, the same cost and indemnity were chosen for the case of a risk-increasing input. It is important to note that, by choosing $m = m_{RD} = m_{RI} = 8$ and $I = I_{RD} = I_{RI} = 48$, the insurance fully covers losses only in the risk-decreasing input case.[21]

5. Empirical analysis

We first present the sample and sessions (Section 5.1.), followed by some summary statistics on subjects' risk preferences (Section 5.2.). Finally, we present the estimation results (Section 5.3.). Summary statistics on input use are presented in Appendix D.

5.1. Sample and sessions

The experiment comprised eight sessions (see Appendix E) conducted at the Montpellier Experimental Economics Laboratory (LEEM) in November 2016 and March 2017.[22] Subjects were recruited from within the subject pool of the LEEM, which consists mainly of students. Our final sample included 137 subjects who were randomly assigned to a session. Subjects enrolled in sessions involving a risk-decreasing input and those playing with a risk-increasing input did not differ much in age (mean: 25 years in the risk-decreasing input sessions and 25.2 years in the risk-increasing input sessions) but differed a little in gender (50.7% male subjects in the risk-decreasing input sessions and 57.6% in the risk-increasing input sessions).

[19] The indemnity and the premium are denominated in production units for simplicity as in Miranda (1991) and Skees, Black and Barnett (1997).

[20] The cost of insurance and the indemnity were chosen as follows. Consider the risk-decreasing input case. At the theoretical optimal input use ($x^* = 347$), the output in the average state is 116 while it is 60 in the bad state of nature. The difference 116-60=56 defines the indemnity. Given the relationship between the indemnity and the cost of insurance, the cost of the insurance should be 9.33 ECUs. In order to make the instructions simpler and to insure that the average yield curve is always above the low yield curve in the insurance treatment, we set $m_{RD} = 8$ and $I_{RD} = 48$.

[21] The insurance we designed in the experiment is a partial insurance in the risk-increasing input case. To fully cover losses with a risk-increasing input, the cost of the insurance and the indemnity should have been set at: $m_{RI} = 15$ output units and $I_{RI} = 90$ output units.

[22] We used the LE2M software developed at the CEE-M (http://www.cee-m.fr/leem/).

5.2. Risk preferences

Risk preferences are elicited from the row at which subjects switch from lottery A to lottery B. A total of 103 subjects (75% of the sample) were found to be risk-averse (see Appendix F). Inconsistency in behaviour was observed for nine subjects (out of 137): one subject switched to lottery B in row 1 in the risk-increasing input sessions, four subjects in the risk-decreasing sessions and four other subjects in the risk-increasing input sessions did not switch to lottery B in row 11.[23] A simple mean test indicates that the average risk aversion of subjects who played with a risk-increasing input is not statistically different from the average risk aversion of subjects who enrolled in the sessions involving a risk-decreasing input.

5.3. Estimation results

We compare the subjects' choice in terms of input use (x) under three different policy settings with three dummy variables indicating the treatments: *BENCH*, *SUB* and *SUB&INS*. We focus on risk-averse subjects. Risk aversion is used as an explanatory variable and measured as an ordered variable (named *AVERSION*) taking values from 1 (moderately risk averse, switching at row 5) to 6 (highly risk averse, switching at row 11).

We estimate the model separately for those subjects who were presented with a risk-decreasing input and for those who were presented with a risk-increasing input. In what follows we consider the six decisions made by the subjects when exposed to any treatment. In each model, we control the timing of decisions (using a variable called *ROUND* that takes discrete values from 1 to 6) and the subject's unobserved heterogeneity through individual-specific effects.[24]

The regression model has the following general form:

$$x_{it} = f\left(TREATMENT_i, AVERSION_i, ROUND_t, H_i\right) + \mu_i + \varepsilon_{it}$$

[23] The subject who switched in row 1 is classified as extremely risk loving. The other subjects are classified as extremely risk averse except for those who also switched before row 11. For the latter, we measure their risk aversion by their first switching point. We keep the nine subjects in the whole sample but only four remain when we restrict the analysis to risk-averse subjects. We ran the regressions without these four subjects. Results do not change much except for the significance of the age parameter.

[24] We tried and estimated alternative models considering the first round decision only as well as models considering the decision made in the last round. The overall model quality was always better when considering all six decisions made by each subject.

where the variable *TREATMENT* features either *BENCH*, *SUB* or *SUB&INS* and *H* represents the vector of subject-specific characteristics (here age and gender of the subject, with *AGE* measured in years and a *MALE* variable taking the value 1 if the subject is a male, and 0 otherwise). The index *i* is for subjects and the index *t* is for rounds. The terms μ_i and ε_{it} are assumed random and feature individual-specific effects and an idiosyncratic error term, respectively. Several interactions between the explanatory variables were tried but only the models with the best overall quality are reported. All models were estimated using Generalised Least Squares and standard errors were adjusted to account for possible correlations among residuals within each session.

The case of a risk-decreasing input

In Model 1-RD we compare the quantity of input x chosen under the no-policy case (*BENCH* treatment) and under the case of a lump-sum subsidy (*SUB* treatment). Model 1-RD is estimated from a total of 622 observations, corresponding to decisions made by 52 different subjects.[25] Estimated coefficients are shown in the left panel of Table 2. The overall R-squared is 0.14 and the between-R-squared is 0.23.

[25] Two records were lost following a technical problem in one of the experimental sessions: 52 subjects x 6 rounds x 2 treatments minus 2 observations = 622 observations in total.

Table 2. Estimation results, case of a risk-decreasing input

	Model 1-RD *BENCH* vs. *SUB*			Model 2-RD *SUB* vs. *SUB&INS*		
	Coef.	Clustered Std. Err.	P>z	Coef.	Clustered Std. Err.	P>z
ROUND	-	-	-	-0.243	2.447	0.921
BENCH x ROUND	10.196***	2.611	0.000	-	-	-
BENCH x AVERSION	20.549**	7.319	0.005	-	-	-
SUB	50.189	30.873	0.104	-	-	-
SUB x AVERSION	18.700***	1.104	0.000	17.995***	1.122	0.000
SUB&INS	-	-	-	-56.798***	10.613	0.000
SUB&INS x AVERSION	-	-	-	31.469***	4.707	0.000
AGE	-4.029***	0.723	0.000	-3.719***	0.624	0.000
MALE	14.022	17.276	0.417	3.716	12.772	0.771
CONSTANT	263.537***	52.342	0.000	315.133***	23.787	0.000
# Observations	622			467		
# Subjects	52			52		
R-squared (overall)	0.14			0.15		
R-squared (between)	0.23			0.24		

We then compare in Model 2-RD input choices with a lump-sum subsidy (*SUB*) and a lump-sum subsidy combined with mandatory insurance (*SUB&INS*). Model 2-RD is estimated on a total of 467 observations corresponding to decisions made by 52 different subjects.[26] Estimated coefficients are shown in the right panel of Table 2.[27] The overall R-squared is 0.15 (between R-squared is 0.24).

In both models, we find that younger subjects chose lower quantities of the risk-decreasing input. Gender is not found to be significant. The timing of decisions (*ROUND*) is found to impact on the input choices of subjects only in the benchmark or no-policy treatment (*BENCH*), as shown by the statistically significant coefficient of the interaction term *BENCH x ROUND* in Model 1-RD, and probably because the benchmark treatment was

[26] In the *SUB* treatment, the first round (in the *BENCH* treatment) was lost for one subject so that the number of observations is: 52 subjects x 6 rounds minus one observation = 311 observations. In the *SUB&INS* treatment, we have 26 subjects x 6 rounds = 156 observations.

[27] Records from one session were lost following a technical problem in the laboratory.

always played first. More precisely, input use increases by an average of 10 units each time subjects take the next decision and when there are no policies in place (which corresponds to an increase in input use of about 3-4% in each round).[28] The positive trend in input use is a common phenomenon in experiments where subjects learn how to play in the first rounds of the game.

We find that more risk-averse subjects use more of the risk-decreasing input in the benchmark, compared to less risk-averse subjects, which confirms hypothesis H1-b. A marginal increase in risk aversion (that is, when risk aversion increases by one unit) leads to an increase in input use estimated at around 20 units (coefficient of *BENCH x AVERSION* significant at the 1% level in Model 1-RD). Stated differently, an increase of one unit on the risk-aversion scale (which varies from 1 to 6) translates into a 7% increase in input use, on average.

Compared to the benchmark or no-policy situation, offering a lump-sum subsidy increases the use of the risk-decreasing input by an average of 50 units or 19%, but the coefficient of the dummy variable *SUB* is significant only at the 10.4% level in Model 1-RD. If subjects behaved as the expected utility model predicts, then this weak finding suggests that their preferences were characterised by IARA (hypothesis H2). Indeed, subjects became wealthier after the provision of a lump-sum subsidy and, in turn, increased their use of a risk-decreasing input, which suggests that their risk aversion increased after receiving the lump-sum payment. The positive effect of the lump-sum subsidy on the quantity of input used increases with the level of risk aversion as shown by the positive coefficient of the interaction term *SUB x AVERSION* in Model 1-RD (the marginal impact is close to 20 units and is significant at the 5% level).

We find that providing mandatory insurance leads to an overall increase in the use of the risk-decreasing input compared to the case with a lump-sum subsidy only (Model 2-RD). The direct impact is negative and estimated at -56 units (significant at the 1% level) but the cross-term with the level of risk aversion is positive (+31). The overall effect of the mandatory insurance is thus negative for a low risk aversion (*AVERSION*=1) and then positive for higher risk aversion levels (*AVERSION*>2). This finding contrasts with the prediction of the

[28] The average input use (on the sample) in the no-policy scenario is 253 units.

third hypothesis (H3) that, with a lump-sum subsidy and mandatory (actuarially-fair) insurance, and compared to the case of a lump-sum subsidy only, risk-averse subjects should choose a lower level of the risk-decreasing input.[29]

The case of a risk-increasing input

For the case of a risk-increasing input we only show estimation results for Model 1-RI comparing input use under the no-policy scenario (*BENCH* treatment) and input use when a lump-sum subsidy is offered to the subjects (*SUB* treatment); see Table 3. The overall quality of Model 2-RI comparing the case of a lump-sum subsidy (*SUB* treatment) to the case of a subsidy and mandatory insurance (*SUB&INS* treatment) is too low for results to be reported. Recall that the insurance we designed in the experiment is a partial insurance in the risk-increasing input case so the insurance might have been too low for subjects to change their input use behaviour. Model 1-RI was estimated using 612 observations corresponding to choices made by 51 subjects.[30] The overall R-squared is low so results have to be interpreted with caution. There are few statistically significant coefficients and none of the interaction terms were found to be significant and were thus removed.

As in the case of a risk-decreasing input, we find that the quantity of input that is chosen by subjects increases over time (when moving from one decision to the next) in the no-policy situation, by an average of 21 units each time (which represents about 8% of the average input use in the benchmark situation on the sample). Hypothesis H1-a is not verified since risk aversion is not statistically significant. When getting a lump-sum subsidy, subjects are found to increase input use by about 100 units or 41% (statistically significant at the 5% level), the largest effect obtained so far. This finding would suggest that this pool of subjects has risk preferences characterised by DARA. Gender and age are not statistically significant.

[29] Studies in the empirical literature usually agree on the very small impact of insurance on agricultural production choices including input use (e.g., Claassen, Langpap and Wu, 2017; Goodwin, Vandeveer and Deal, 2004; Goodwin and Smith, 2003; Wu, 1999). However these studies did not explicitly take risk preferences into account when specifying models describing farmers’ decisions so they are not directly comparable to ours.

[30] These 51 subjects are different from the 52 subjects who were exposed to the risk-decreasing input case.

Table 3. Estimation results, case of a risk-increasing input

	Model 1-RI *BENCH* versus *SUB*		
	Coef.	Clustered Std. Err.	P>z
BENCH x ROUND	21.175**	8.281	0.011
AVERSION	-3.741	10.980	0.733
SUB	104.298**	41.821	0.013
AGE	0.153	3.077	0.960
MALE	13.664	54.446	0.802
CONSTANT	203.399**	80.648	0.012
# Observations	612		
# Subjects	51		
R-squared (overall)	0.04		
R-squared (between)	0.01		

6. Conclusion

In this article we describe an experiment designed so that it allows full control over the production technology and production risk. By doing this we are able to disentangle the impact (on input choices) of the technology and production risk, from the impact of risk preferences. This study illustrates the usefulness of laboratory experiments in settings where identification of risk preferences using observational data and structural models is difficult (see Bellemare and Lee, 2016, for related discussions in the context of price risk).

The subjects could manage part of the production risk through the quantity of input that they purchased. We consider two separate cases of a risk-increasing input and a risk-decreasing input. The experiment is not framed in an agricultural context, but the production technology is specified such that the parameters of both the mean and variance functions are in the range of those estimated using farm data. The analysis focuses on the subset of risk-averse subjects who make input purchase decisions after visualising (on graphs displayed on the screen) the impact of their choices in terms of total output and realised profit in the three possible states of nature.

We derive some theoretical predictions on the relationship between risk preferences and input choice cases. We first consider a benchmark situation without any public policies and we then study how a lump-sum subsidy, as a single instrument and then combined with mandatory insurance, influences input decisions. First-order conditions on input use are derived under the assumption that subjects' decision making under uncertainty is adequately described by the expected utility model, the most common model used so far in the agricultural economics literature to describe the behaviour of farmers facing risk and uncertainty.

Theoretical predictions are only partially confirmed in the case of a risk-decreasing input. Our findings show that more risk-averse subjects use more of the risk-decreasing input in the benchmark but we do not find any statistically significant impact of risk aversion on input use in the case of a risk-increasing input. This (non-)result might be explained by the flatness of the agricultural production and profit functions in the region around the optimum, which implies that even large changes in input use may induce only limited variation in expected profit. A wide plateau in the expected payoff function also generally implies flatness of the "certainty equivalent" function (i.e., the expected profit minus the risk premium) and hence translates into a limited impact of risk aversion on farmers' welfare overall (Pannell, 2006). This finding raises broader questions about the sensitivity of optimal input choices and farmers' overall welfare to risk preferences. Knowing the inherent difficulty of identifying risk preferences using observational data (Just and Just, 2011), greater attention and effort should be put on understanding the implications of flat payoff (and certainty equivalent) functions as recommended by Pannell (2006). In studies involving risk and uncertainty, agricultural economists should consider measuring the importance of risk preferences on payoffs and welfare, and assessing whether risk preferences have to be taken into account and modelled. A wrong representation of risk preferences might, in some cases, lead to recommendations for the design of agricultural and environmental policies that are more misleading than those which would have been derived under the assumption of risk-neutral preferences. The importance of modelling risk preferences needs to be assessed on a case-by-case basis but the question should definitely be considered more systematically by agricultural economists.

Regarding the impact of public policies, our results show that subjects adjust their input use in response to the introduction of an unconditional and lump-sum subsidy (though weakly for risk-decreasing inputs), which may be an indication that subjects are not CARA. The size of our sample did not allow us to examine further heterogeneity in the structure of risk preferences. The provision of mandatory insurance has a significant impact on input use in the case of a risk-decreasing input, but our findings (in terms of the direction of the impact) are not in line with theoretical predictions for most of the observed levels of risk aversion. The non-significant impact of the insurance in the risk-increasing case might be explained by the fact that the insurance does not provide full coverage in this case. The rejection of some of the theoretical predictions might suggest that models that are more flexible than the expected utility model should be considered to describe producers' decisions under uncertainty (see e.g. Liu and Huang, 2013; Bocquého, Jacquet and Reynaud, 2014; and Bougherara et al., 2017, for use of alternative models such as those derived from the prospect theory).

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Appendix A. Experimental instructions for the *BENCH* treatment for a risk-decreasing input

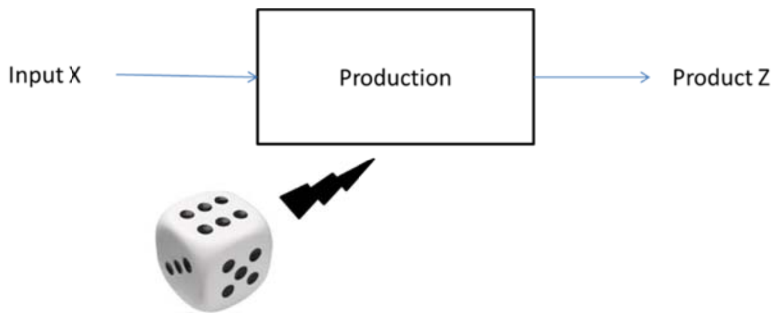
In this task, there will be six rounds.

You are a producer. Your objective is to make the highest profit. The currency conversion rate will be: 2,000 ECUs=1 Euro and 1 ECU=0.0005 Euros.

You produce a product called *product Z* using an input called *input X*. Every unit of product Z that you produce will be bought from you in the experiment at a unit price of 10 ECUs.

You need to choose the quantity of input X you want to use to produce product Z. The quantity of product Z is a function of the quantity of input X. Input X will cost you 1 ECU per unit.

The yield of product Z is random. You do not know for certain how much of product Z you will get from using a chosen quantity of input X. The quantity of product Z you will get depends on the quantity of input X chosen and on the result of rolling a dice.



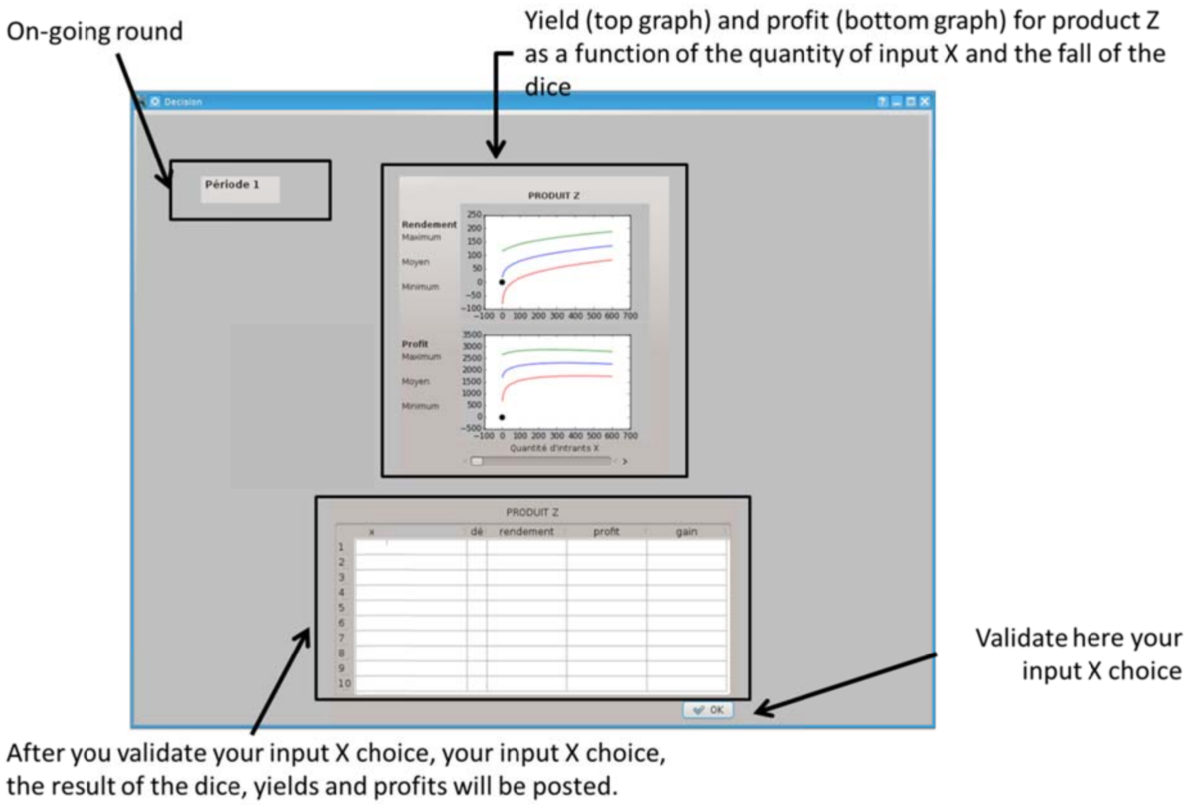
There will be six rounds. At the beginning of each round, you will receive a bonus of 1,500 ECUs. Then, you need to choose the quantity of input X you want to use to produce product Z. Next, you will roll a dice on the computer. Given the result of the dice and the level of input X you chose, the yield and profit for product Z will be computed.

On the screen, you will be presented with three panels:

- a panel indicating the on-going round (from 1 to 6);

- a panel indicating yields and profits for product Z for each level of input X and each roll of the dice, where you will need to choose the level of input X;

- a panel summarising, after you validate your choice of input X, the level of input X, the fall of the dice, the subsequent yield and profit for product Z and your gains for the round;



Yields and profits for product Z are a function of the level of input X you choose (scroll bar) but also of the result of rolling a dice. The green curve will apply if the result of the dice is 1. The blue curve will apply if the result of the dice is 2, 3, 4 or 5. The red curve will apply if the result of the dice is 6.

Notice that the three curves for profits reach a maximum for different levels of input X:

- The red curve is maximum for an input X level of 261.
- The blue curve is maximum for an input X level of 347.
- The green curve is maximum for an input X level of 419.

Notice also that the higher the quantity of input X, the more the three curves converge.

The profits on the screen are computed as follows:

Profit for product Z	=	Price of product Z (10 ECUs)	x	Quantity of product Z	-	Price of input X (1 ECU)	x	Quantity chosen of input X	+	Bonus (1,500 ECUs)

Appendix B. Incentives and order effects

In experimental economics subjects are commonly incentivised through payments and the choice which determines the payment is usually randomly chosen in order to maintain incentives and to avoid wealth effects (i.e., payoff accumulation from one round of the game to the next). In our experiment, all subjects played four games: the risk elicitation task (11 choice situations) and three treatments in the production task (six rounds in each treatment). One of these four games was randomly drawn. If the risk elicitation task was selected, then a choice situation (1 to 11) was randomly drawn and the lottery chosen by the subject in that particular row was played for payment. If the game that was drawn was one of the three treatments, a round (1 to 6) was randomly drawn and the subjects' input choice, the fall of the dice and the endowment in that particular round and for that particular treatment determined the payment.

One concern in experiments using a within-subject design is order effects. In our setting, subjects always played the risk elicitation task first. One concern could be that results in the production task would differ had the risk elicitation task been played after the production task. This would be a concern if our aim were to study the absolute level of input use in a specific treatment. However, we are primarily interested in relative input choices; that is, the impact (on subjects' input use) of introducing a subsidy versus the no-policy scenario, or the impact of coupling mandatory insurance to a subsidy versus the case of a subsidy only. So, even if order effects are at play, this is not a concern in our study. Besides, order effects may also play a role in the treatments. In all cases the benchmark treatment was played first, followed by the subsidy treatment, and finally the insurance treatment. Results might differ if subjects had played the three treatments in a different order but we are interested in the impact of the introduction of a policy and not in its removal. So order effects for treatments are also not a concern in our study.

Appendix C. Risk elicitation task

In what follows the 11 lottery choices are indexed by $j = 1, \ldots, 11$. Lotteries A and B (see Table C.1.) are characterised by: $\{(p_j, y_H^A, y_L^A); (p_j, y_H^B, y_L^B)\}$. Lottery A offers a high outcome y_H^A with probability p_j and a low outcome y_L^A with probability $(1 - p_j)$. Lottery B offers a high outcome y_H^B with probability p_j and a low outcome y_L^B with probability $(1 - p_j)$. Outcomes are expressed in Experimental Currency Units (ECUs). The conversion rate in the risk elicitation task is 1 Euro for 1 ECU. The choices that subjects made allowed us to elicit their degree of risk aversion. A risk-neutral subject would choose lottery A in rows 1 to 5 and lottery B in rows 6 to 11 because the expected value of lottery A exceeds the expected value of lottery B in the first five rows. A risk-loving subject switches earlier while a risk-averse subject switches later.

Table C.1. Multiple price list for risk preference elicitation adapted from Holt and Laury (2002) (subjects are not shown the last column) – outcomes in ECUs

Row	Lottery A				Lottery B				Difference in expected value between B and A
	p_j	y_H^A	$(1-p_j)$	y_L^A	p_j	y_H^B	$(1-p_j)$	y_L^B	
1	0	20	1	16	0	38.5	1	1	-15
2	0.1	20	0.9	16	0.1	38.5	0.9	1	-11.65
3	0.2	20	0.8	16	0.2	38.5	0.8	1	-8.3
4	0.3	20	0.7	16	0.3	38.5	0.7	1	-4.95
5	0.4	20	0.6	16	0.4	38.5	0.6	1	-1.6
6	0.5	20	0.5	16	0.5	38.5	0.5	1	1.75
7	0.6	20	0.4	16	0.6	38.5	0.4	1	5.1
8	0.7	20	0.3	16	0.7	38.5	0.3	1	8.45
9	0.8	20	0.2	16	0.8	38.5	0.2	1	11.8
10	0.9	20	0.1	16	0.9	38.5	0.1	1	15.15
11	1	20	0	16	1	38.5	0	1	18.5

Appendix D. Summary statistics on input use

As shown in Hill and Viceisza (2012), earlier draws of the random variable (i.e., the outcome of rolling the dice) may impact input use in subsequent rounds. For our descriptive analysis to be free of any trend (such as a possible learning effect), we analyse decisions made in round 1 only. We also consider solely decisions made by risk-averse subjects.[31] Figure D.1. shows input use in each treatment as a function of input type. Table D.1. provides some summary statistics and a non-parametric test to compare input use between treatments.

We first note that input use, at the mean, is always lower than (or equal to) the theoretically-optimal input level under risk-neutrality. This is as predicted by the theory for the case of a risk-increasing input when the subject is risk averse but contrary to what the theory predicts for the case of a risk-decreasing input. Hypothesis H1-a is thus only (partially) verified by our data.[32] According to hypothesis H2, subjects are CARA in the risk-decreasing input sessions (no significant impact of the subsidy) and DARA in the risk-increasing sessions (positive and significant impact of the subsidy). Finally, we find no support for hypothesis H3 on the impact of a subsidy and insurance (no significant impact).

[31] The four hypotheses (H1-a, H1-b, H2 and H3) were derived under the assumption that individuals are risk averse. Also farmers are found to be risk averse in most situations and the pool of risk-loving subjects in our experiment is rather small.

[32] We only consider choices made in round 1. Although our theoretical model does not allow for learning effects, behavioural issues may be at play. It is commonly observed that subjects learn over the rounds and that they do not reach the optimal decision in the first round. This may also happen here.

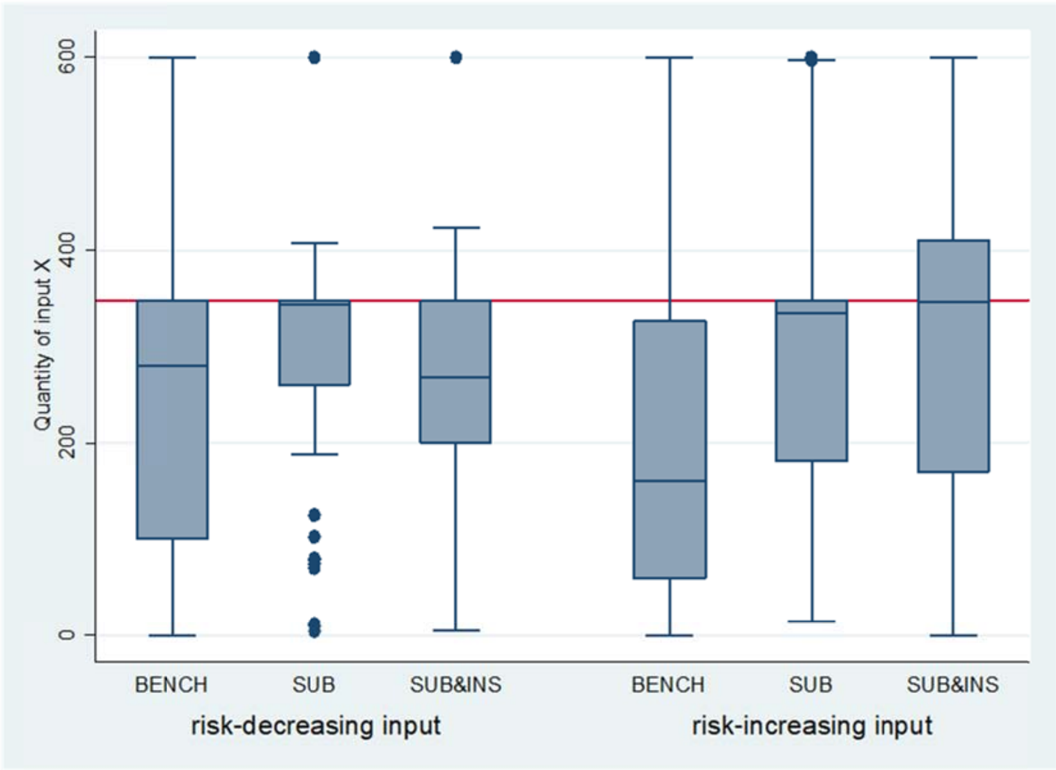


Figure D.1. Input use in each treatment as a function of the type of input for risk-averse subjects in round 1 (horizontal line represents the theoretical prediction for a risk-neutral agent)

Table D.1. Input use in each treatment as a function of the type of input for risk-averse subjects in round 1 and the Wilcoxon ranksum test

Treatment	Risk-decreasing input				Risk-increasing input			
	#Subj.	*Mean*	*Std Dev*	*Test*	*#Subj.*	*Mean*	*Std Dev*	*Test*
BENCH	52	253.02	163.96		51	197.06	156.62	
SUB	51	284.82	128.10	0.3826[a]	51	300.61	152.00	0.0007[a]
SUB&INS	26	263.38	139.50	0.3629[b]	27	318.00	181.85	0.5989[b]

[a]: *p-value* of the test of *SUB* vs. *BENCH*; [b]: *p-value* of the test of *SUB&INS* vs. *SUB*.

Here, we only considered decisions made in round 1. In the econometric analysis, we take into account all six decisions made by each subject, which allows us to control for individual-specific effects.

Appendix E. Sessions

Table E.1. Sessions

Session	Input	Risk Attitude Elicitation	Treatment			#Subj. (137)	#Obs. (2,064)
1	Risk-decreasing	Multiple price list, Binary lottery choices	*BENCH* (6 rounds)	*SUB* (6 rounds)	–	16	192
2	Risk-decreasing	Multiple price list, Binary lottery choices	*BENCH* (6 rounds)	*SUB* (6 rounds)	*SUB&INS* (6 rounds)	15	270
3	Risk-increasing	Multiple price list, Binary lottery choices	*BENCH* (6 rounds)	*SUB* (6 rounds)	–	16	192
4	Risk-increasing	Multiple price list, Binary lottery choices	*BENCH* (6 rounds)	*SUB* (6 rounds)	*SUB&INS* (6 rounds)	15	270
5	Risk-decreasing	Multiple price list, Binary lottery choices	*BENCH* (6 rounds)	*SUB* (6 rounds)	–	20	240
6	Risk-decreasing	Multiple price list, Binary lottery choices	*BENCH* (6 rounds)	*SUB* (6 rounds)	*SUB&INS* (6 rounds)	20	360
7	Risk-increasing	Multiple price list, Binary lottery choices	*BENCH* (6 rounds)	*SUB* (6 rounds)	–	15	180
8	Risk-increasing	Multiple price list, Binary lottery choices	*BENCH* (6 rounds)	*SUB* (6 rounds)	*SUB&INS* (6 rounds)	20	360

Appendix F. Summary statistics on risk preferences

The theoretical prediction for risk-neutral individuals (dotted line) is to always choose lottery A in rows 1 to 5 and lottery B in rows 6 to 11. Consider rows 1 to 5. The share of subjects is lower than 100% which indicates that some subjects displayed risk loving by switching earlier than the risk-neutral prediction. In rows 6 to 11, the share of subjects is higher than the theoretical risk-neutral prediction, which is evidence for risk aversion.

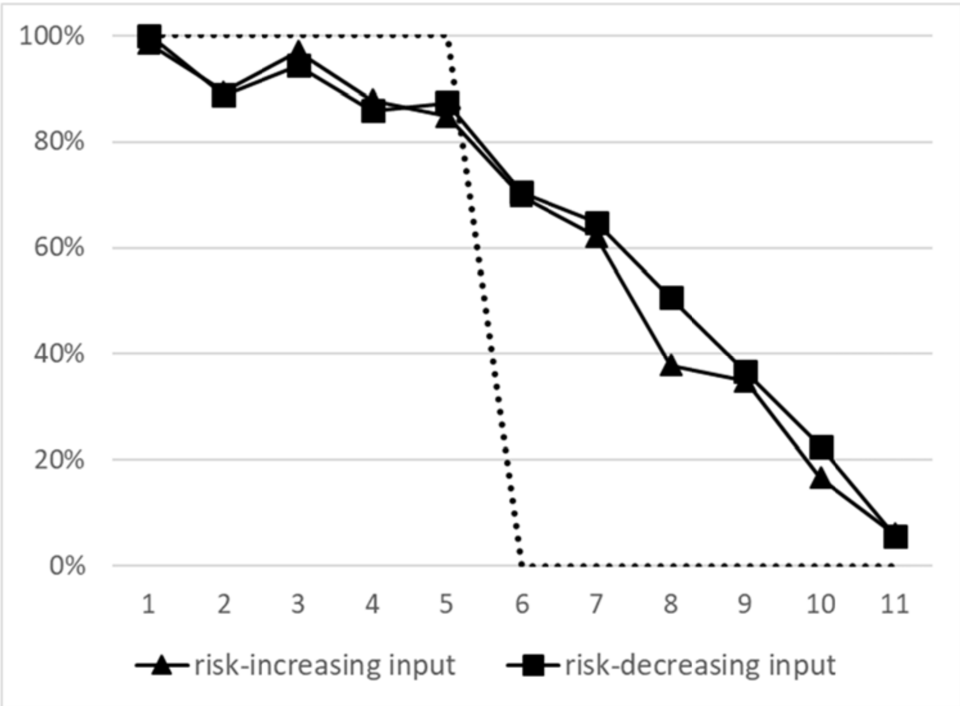


Figure F.1. Share of subjects choosing lottery A in each row (1 to 11) according to the type of input (dotted line represents the theoretical prediction for risk-neutral subjects)