Pesticide use and agricultural risk.
The case of rice producers in Vietnam.

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Abstract

The excessive and unsustainable use of pesticides has generated concern due to their potential detrimental effects on farmers' health, environment and agricultural sustainability. Thus, the overuse of chemical pesticides remains an important development issue, and understanding pesticide input decisions is a key requisite to sound policy-making. This paper examines risk effects of pesticide use by applying a lottery game in combination with a more traditional production function approach employing a dataset on rice producers in Vietnam. Using pest and water shortage shock events for identification, production function results show that an increase in pesticide use can make production more risky. This result is supported by the lottery approach showing that more risk averse farmers use less pesticide, implying that pesticide is a risk-increasing input. Our results suggest that higher rainfall uncertainty (relative to pest) is likely to drive the risk increasing effect of pesticides. This highlights the importance of considering multiple uncertainties when determining risk properties of agricultural inputs.

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Key words: pesticide, risk effect, shocks, lottery, Just-Pope production function

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1 Introduction

The adoption of yield-enhancing chemical inputs such as pesticides has broadly been promoted in developing countries as a manner to boost agricultural productivity (Fernandez-Cornejo et al., 1998). However, the excessive and unsustainable use of toxic pesticides has created concerns due to its detrimental effects on health, the environment and agricultural sustainability (Pimentel et al. 1992; FAO, 2001). These negative effects include damage to agricultural land, fisheries, fauna and flora, and destruction of natural predators of pests. Furthermore, increased mortality and morbidity of humans due to exposure to pesticides are also recorded to be important (Antle and Pingali, 1994; Crissman et al., 1994; Pingali et al., 1994). These concerns are even more serious in developing countries due to lower skill/knowledge levels, limited provision of extension services to disseminate less intensive pesticide practices, financing constraints with regards to acquisition of suitable safety equipment, and a weak legislation (Wilson and Tisdell, 2001).

Use of pesticides is remarkably high in Asian economies (Pingali et al., 1994). In particular, it has more than tripled in Vietnam since 1990, and pesticide regulation has not evolved accordingly as it remains far less rigorous than pesticide regulations in more advanced economies (Phung et al., 2012).[2] Consequences on farmer's health have been reported to be serious (Dasgupta et al., 2007), and it has also been found that farmers overuse pesticide inputs beyond the economic optimum (Dung and Dung, 1999; Huang et al., 2002; Pemsl et al., 2005). Thus, understanding the overuse of pesticides remain an important issue, and is for Vietnam in line with the challenge of entering into a new development phase, in which sustainability of agriculture production and the environment are fundamental pillars (World Bank, 2011).

This paper analyzes the relationship between pesticide use and farmer specific risk characteristics, which is key for understanding pesticide input choices. A risk-reducing input is normally identified through two distinct characteristics observed in data (Quiggin, 1991): First, an input is labelled risk reducing when its use reduces the variance of production. Second, all else equal, a risk averse producer would use more risk-reducing inputs than a risk neutral one.[3] Empirical evidence using

[2] Since the early 1990s, the Plant Protection Department of Vietnam's Ministry of Agriculture and Rural Development is in charge of the pesticide management, including the approval, restriction, and prohibition of chemicals.

[3] Quiggin (1991) also argues that a producer with output insurance using less pesticide may also be consistent with the risk-reducing view. However, the evidence for this mechanism is mixed (Horowitz and Lichtenberg, 1993; Babcock and Hennesey, 1996; and Smith and Goodwin, 1996). Moreover, agriculture insurance is rather new in Vietnam; the government started a pilot program in 2011. Recent surveys (CIEM et al., 2011; 2013) have not found substantial adoption of such insurance, and in the following we therefore do not test this potential mechanism.

either approach is mixed. However, while most of the production variance studies obtain results consistent with the notion of pesticide being risk-increasing (see for example Regev et al., 1997; Shankar et al., 2008; Krishna et al. 2009), recent studies using lotteries to elicit risk aversion support the risk-decreasing view (Gong et al., 2012; Liu and Huang, 2013). In this paper, we test the risk effects of pesticide use by using both the lottery (experimental) and the production function (econometric) approach on a sample of farmers in Vietnam. To our knowledge, no empirical studies exploring the consistency regarding the risk property of pesticides using identical samples have been done previously in the literature. Furthermore, Horowitz and Lichtenberg (1994) argue that risk effects of pesticide use may be determined by an interaction of multiple sources of uncertainty. The importance of these sources can vary across different farming activities, locations and periods. With the exception of Shankar et al. (2008), empirical evidence regarding this aspect remains quite scarce. In this paper, we therefore also investigate the source of this risk effect by using information on the occurrence of pest and drought shocks to proxy for bad and good states of nature with regards to pest density and rainfall in rice farming, respectively.

The rest of the article is organized as follows: Section 2 describes characteristics of the agriculture sector, pesticide use and shocks in Vietnam; Section 3 reviews a conceptual framework that links pesticide use, risk-taking behavior and shocks; Section 4 presents the data used; and section 5 the econometric model; Section 6 discusses the main results; Section 7 considers a number of robustness tests; and Section 8 concludes.

2 Agriculture, shocks and pesticide use in Vietnam

Agriculture is the most important economic activity in terms of job creation in Vietnam, and constitutes the main source of livelihood for around 70% of the population. Paddy rice production is one of the main agricultural activities, covering 65% of the area under cultivation. Rice has long been the major source of food and income for rural households. Many farmers both consume and sell their rice, which is typically grown two to three times per year on small landholdings formed by multiple plots (Phung, 2012). Rice production remains a labor intensive practice, with most workers being family members, but some farms hire extra labor and rent mechanized equipment. Rice farming requires significant amount of water to flood the fields. For instance, producing one kilogram of unprocessed rice in Vietnam is estimated to use on average 2.500-3.000 liters of water

(Chu Thai, 2013). Since the flooded condition of rice fields is necessary for rice growth, drought events become one of the most important sources of risk in rice production.

Pest infestation is also a substantial source of risk. If left unmonitored, it can cause enormous productivity losses or even in some cases it can lead to total crop failure. Vietnamese farmers have tackled this problem by increasing the use of pesticides. In fact, more than 95% of farmers report to apply some variety of pesticides on their crops (CIEM et al., 2011; 2013). To illustrate, the use of chemical inputs rose from 14,000 tons under 837 trade names in 1990 to 50,000 tons under more than 3,000 trade names in 2008 (Phung et al., 2012). Even though agricultural pesticide use has played a crucial role in expanding rice cultivation and enhancing rice productivity in Vietnam, incorrect pesticide application, including too frequent, more toxic[4] and excessive quantities of pesticide is common among Vietnamese farmers (Dung and Dung, 1999; Klemick and Lichtenberg, 2008).[5] The lack of knowledge about the manipulation and the correct use of safety clothing is also an issue of public concern (Meisner, 2005).[6] An improper manipulation, storage and disposal of pesticide jointly with weak pesticide law enforcement and an inadequate use of protective equipment put farmers at high risk of being harmed by pesticide exposure. Accordingly, hospital records,[7] self-reported farmer data and medical tests suggest a high prevalence of pesticide poisoning in Vietnam. For example, Murphy et al., (2002) found that around 30% of a sample of farmers surveyed in a village in Nam Dinh province in northern Vietnam reported to suffer from at least one symptom of pesticide poisoning. Similar evidence of acute pesticide poisoning was shown by Dasgupta et al. (2007) in a sample of farmers tested for blood cholinesterase in several districts in the Mekong Delta region in southern Vietnam. The most common short-term health effects were associated with dermal (skin irritation), ocular (eye irritation), neurological (headaches, dizziness and insomnia) and respiratory symptoms (exhaustion, shortness of breath and sore throat).[8] Training and farmer field school programs in Integrated Pest Control Management (IPM) have been

[4] Pesticides classified as highly toxic according to the World Health Organization (WHO) such as carbofuran, endosulfan, methamidophos, monocrotophos, and methyl parathion are banned in Vietnam. However, farmers have been found to still apply these chemical classes on their fields (Meisner, 2005).

[5] When not considering toxicity information on pesticides, on average, it is found that non-poor farmers use significantly larger quantities of chemical pesticide than the poor.

[6] The use of protective clothing such as gloves, glasses and shoes is not common among Vietnamese farmers. Apart from usual budget constraint arguments that make protective clothing unfordable for the poorer, other reasons include farmers' reluctance to wear safety clothing since they consider it uncomfortable or inappropriate when having to work under high temperatures.

[7] Health problems may be underestimated by official figures because many cases are never registered in hospitals and health centers. The most common reasons for that are erroneous diagnostics since pesticide poisoning can mimic other common health problems, reluctance to see a doctor because of fear that drawing attention to themselves can result in the loss of their job or simply budget constraints to afford adequate medical attention.

[8] There are also potential and less understood long-term health effects of using pesticides that may emerge only year to decades later. For example, a variety of pesticides are considered carcinogens, while others are associated with poor reproductive outcomes, neurologic and respiratory disorders, and impairment of the immune system (WHO, 1990).

implemented to make farmers aware about the risks of pesticide use for human health and the environment. These programs are aimed at promoting the use of alternative pest control actions through more closely monitoring and use of natural enemies. Furthermore, the government has also tried to convince farmers to refrain from insecticide sprays after rice seeding through massive campaigns. The main goal of these programs has been to decrease pesticide use, particularly the use of the most toxic chemicals. However, pesticides continue to be used broadly in rice farming beyond sustainable levels (Klemick and Lichtenberg, 2008). In this paper we focus on the production risk effect of pesticide use to understand this overuse.

3 Conceptual framework

Reducing uncertainty as regards to agricultural output over time has been one of major factors for promoting pesticide use. Pest uncertainty mainly comes from limited information on pest density, severity, chemical dosage needed to deal with it, and effectiveness of pesticide application. The latter has led to increased risk regarding both production yield and profits. Thus, the intuitive reason for applying pesticides is to reduce production risk, which would lead to adoption among capital constrained and relative more risk averse farmers (Federer, 1979). However, an alternative view states that pesticide use may in fact increase risk, arising from uncertainties related to other crop growing conditions (Lazarus and Swanson, 1983; Pannel, 1991). Horowitz and Lichtenberg (1994) demonstrate that the risk effect of pesticides will depend on the interaction and relationship between different types of agricultural uncertainties.

To see this, assume a production function, $f(x_p, \boldsymbol{x}, \varepsilon)$, where x_p denotes pesticide input, $\boldsymbol{x}$ is a vector of all other inputs, and ε is a random production error. Suppose that ε is ordered from bad states to good states of nature, implying that the derivative with respect to the random variable is positive, i.e, $f_\varepsilon(x_p, \boldsymbol{x}, \varepsilon) > 0$. In addition, we assume that pesticides increase production regardless the state of nature, i.e., $f_{x_p}(x_p, \boldsymbol{x}, \varepsilon) > 0$. Following Horowitz and Lichtenberg (1994), pesticide input x_p is risk-decreasing if $f_{x_p\varepsilon}(x_p, \boldsymbol{x}, \varepsilon) < 0$, that is, pesticides increase output more in bad states than in good states of nature. This means that pesticide use is risk-increasing if $f_{x_p\varepsilon}(x_p, \boldsymbol{x}, \varepsilon) > 0$, indicating that pesticide increases output more in good states than in bad states of nature. Quiggin (1991) proves that this definition is equivalent to saying that more risk averse producers use more (less) of a risk-decreasing (increasing) input that less risk averse producers.

When ε mainly represents uncertainty about pest density (and its distribution), one would expect pesticides to raise output more (less) when pest density is high (low), making pesticide use risk-decreasing. However, alternative sources of agricultural production uncertainty, i.e., rainfall, can also be important risk influencing factors, especially in rice production. More importantly, one would expect that pesticide productivity is higher (lower) during high (low) rainfall periods (significantly above predicted averages) since there are more (less) crops to protect, which makes pesticides a risk-increasing input when considering its use in the context of multiple uncertainties. When these multiple sources of uncertainty are highly correlated factors that promote crop growth, also encouraging weeds or insect pest, pesticide use is more likely to be risk-increasing.

Traditionally, testing the risk effect of pesticides has relied on econometric estimations of risk using a production function approach, and the evidence seems to support the risk-increasing view (see for example Regev et al., 1997; Shankar et al., 2008; Krishna et al., 2009). However, recent empirical work using experimental approaches to elicit risk preferences find that more risk averse farmers apply larger quantities of pesticide, supporting the standard view of pesticides being risk-reducing (Gong et al., 2012; Liu and Huang, 2013). From this empirical literature, three fundamental conclusions emerge. First, results seem to be approach-dependent. The latter have been suggested by Reynaud et al. (2010). They found differences in farmers' attitudes elicited by stated and revealed methods, suggesting an effect due to the approach. Nevertheless, they prove some consistency and coherence across experimental and econometric elicitation methods. Second, risk effects have been estimated for a small number of farmers, questioning representativeness such that inconsistencies across approaches may be associated with sample characteristics. Third, differences may be driven by the context in which agricultural decisions take place. Thus, more evidence in favor of the risk-reducing view in some studies may simply reflect that pest density is more of a concern in these locations or was more serious at the time when data was collected. Alternatively, other sources of agricultural production uncertainty may have been more important in studies finding more support for the risk-increasing argument. For example, Shankar et al. (2008) studied the risk properties of Genetically Modified (GM) technology and pesticides among a sample of cotton producers in South Africa, accounting for multiple sources of uncertainty. They found a strong correlation between the random variables capturing rainfall and pest density, which is consistent with theoretical conditions under which the risk-increasing thesis is more likely to hold.[9]

Thus, whether reported differences in results can be attributed to variations in methodologies, sample characteristics, farming activities, locations, etc., is rather difficult to determine. In this paper, we try to overcome this problem and understand these differences, focusing on a sample of rice farmers in the Vietnamese context.

4 Estimation procedure

First, we present the experimental approach to study the risk property of pesticides using a lottery game. Second, we introduce the Just-Pope production function method, broadly used to examine risk characteristics of inputs in agriculture.

4.1 Pesticide input and risk aversion

The first approach consists of setting up an estimating equation in which pesticide input decisions depend on risk aversion. Given the censured nature of our dependent variable measuring pesticide use, we estimate the Tobit model, which assume corner solutions. The model is specified as follows:

$$x_{pi} = max(0, \delta z_i + \varphi w_i + \gamma r_i + u_i), \quad u_i \backslash z_i, w_i, r_i \sim N(0, \sigma_u^2) \tag{1}$$

Where x_{pi} corresponds to a measure of pesticide input applied to a farm i, z_i contains a vector of socioeconomics and farm level characteristics, w_i defines measures of states of nature with regard to pest and other growing conditions, respectively, r_i stands for a measure of risk aversion, and u_i is the normally distributed error term.

The parameters γ and φ are the coefficients of interest. If $\gamma > 0$, more risk averse farmers use larger amount of pesticides, then pesticide is risk-reducing. Similarly, if $\gamma < 0$, farmers who are more risk farmers use less inputs, then pesticide is risk-increasing. Furthermore, if pesticide use is sensitive to the risk environment, φ will be positive (negative) when pest infestation is high (low) and negative (positive) as other growing conditions are bad (good).

[9] For more evidence supporting the risk-increasing argument see Auld and Tisdell (1987), Antle (1988), Pannel (1990), Horowitz and Lichtenberg, (1993), Hurd (1994) and Regev et al. (1997).

4.2 Pesticide input and production risk

In order to investigate the risk effect of pesticides, we alternatively apply the framework outlined by Just and Pope (1979). This approach provides a method for estimating the marginal risk effect of inputs. The Just-Pope (JP) production function is specified as:

$$y_i = f(x_i, \varepsilon_i) = q(x_i, \alpha) + h(x_i, \beta)\varepsilon_i \tag{2}$$

Where y_i is the level of output for farm i, x_i is a vector of inputs for farm i, $q(.)$ is the mean function (or determinist part) that relates inputs to levels of output, α is a vector of parameters attached to the mean function, $h(.)$ is the variance function (or risk part) that associates inputs to output variability, β is the parameter vector attached to the risk function, and ε is the exogenous production shock with mean $E(\varepsilon_i) = 0$ and $Var(\varepsilon_i) = 1$. Defining $Var(y_i) = h^2(x_i, \alpha_i, \beta)$, we can observe that inputs are allowed to influence both mean output and output risk. One key requirement for this specification is that it should not impose any a priori restriction on the effect of inputs on production risk, that is, $\frac{\partial Var(y_{it})}{\partial x_{it}} <=> 0$.

The JP production function (2) is estimated by Feasible Generalized Least Squares (FGLS).[10] First, we estimate the parameters of the mean function $y_i = q(x_i, \alpha) + e^*$. Lichtenberg and Zilberman (1986) argue that pesticide is a damage control input whose contribution lies in their ability to increase the share of potential output by reducing damage from pest infestation. Thus, pesticides input should be treated differently in the production analysis than conventional inputs.[11] Following Krishna et al. (2009), we combine the damage control framework with Just-Pope econometric methods to account for this characteristic. Let us define $G(x_c)$ as the damage abatement function. This function captures the destructive capacity of the damaging agent eliminated by the application of a level of control inputs x_c.[12] By making the distinction between regular inputs x_r and control inputs x_c, the damage-production function is defined as follows: $q(x_i, \alpha) = A \prod_{k=1}^{nr} x_{irk}^{\alpha_k} G(dx_{ci})$, where *nr* now indicates the total number of conventional inputs, and $G(x_{ci}) = [1 - \exp(\mu -$

[10] Saha et al. (1997a) found that the FLGS does not perform well in the case of small samples, and the Maximum Likelihood Estimator (MLE) should be applied as it is more efficient and unbiased. Given the size of our sample, our results should be robust to the use of alternative estimators.

[11] Lichtenberg and Zilberman (1986) found that standard production function specifications overestimate the productivity of damage control inputs.

[12] The abatement function is defined on the (0, 1) interval with G = 1 denoting complete eradication of the destructive capacity and G = 0 denoting zero elimination; it is monotonically increasing; and it approaches a value of unity as damage-control agent use increases.

$\sigma x_{ci})]^{-1}$ is a logistic function.[13] Ease of convergence in the nonlinear least square (NLS) method was the main reason behind this decision.

In the second stage, the parameters of the variance function are estimated by OLS using the predicted residuals from the mean function $\hat{e}_i^* = h(x_i, \beta)\varepsilon_i$ assuming a Cobb-Douglas functional form for $h(x_i, \beta)$.[14] By taking natural logarithms on both sides, and absolute values of $\hat{e}_i^*$ yields:

$$ln|\,\hat{e}_i^*| = \beta + \sum_{k=1}^{n} \beta_k ln x_{ki} \tag{3}$$

Where β_k corresponds to estimates of the risk marginal effect of inputs, $\frac{\partial Var(y_i)}{\partial xk_i}$. If x_{pi} denotes the amount of pesticide input used by farm *i* and β_p the marginal risk effect of pesticides, we have that pesticide is risk-reducing if $\beta_p < 0$, or risk-increasing if $\beta_p > 0$.

In a final stage, since equation (1) is a heteroskedastic regression, we attain asymptotic efficiency in estimation of the parameters α of the mean function by applying weighted regression with incorporating weights $h^{-1}(x_i, \hat{\beta})$.

To test the relative importance of different sources of randomness in determining the risk properties of pesticides, we augmented the mean function including interactions between pesticide inputs and the different uncertainty drivers (i.e. pest and rainfall). In other words, we estimate changes in productivity of using pesticides along states of nature of both pest and rainfall, that is, $f_{x_p\varepsilon_1}(x_p, \boldsymbol{x}, \varepsilon_1)$, and $f_{x_p\varepsilon_2}(x_p, \boldsymbol{x}, \varepsilon_2)$, where ε_1 and ε_2 relates to pest and rainfall, respectively. Thus, pesticide is more likely to be risk-reducing (risk-increasing) when $f_{x_p\varepsilon_1}(.)$ is relatively more (less) important than $f_{x_p\varepsilon_2}(.)$.

5 Data

We use data from the Vietnam Access to Resources Household Survey (VARHS). The VARHSs are longitudinal surveys conducted every second year from 2006 by the Institute of Labor Science

[13] This specification has been used in the literature before, yielding sensible results (see Lichtenberg and Zilberman, 1986; Carrasco-Tauver and Moffit, 1992; Krishna et al., 2009)

[14] Alternative specifications such as linear and quadratic forms were also considered for the variance function. Results remain the same, however. Details can be obtained under request.

and Social Affairs of the Ministry of Labor, Invalids and Social Affairs with the technical support from Department of Economics at the University of Copenhagen. This survey constitutes one the main data sources on the current state of the rural population of Vietnam regarding access to productive resources. Data collection is done in rural areas of 12 provinces (covering 161 districts and 456 communes). In particular, the survey collects regularly information on households' demographic characteristics, assets, saving, credit, incomes as well as production, farm inputs and shocks. Lottery questions to elicit risk aversion measures were introduced from the fourth wave of VARHS in 2010 (CIEM et al., 2011; 2013). However, farmers' responses to lotteries in 2012 show inconsistencies that make us suspect about their reliability. Consequently, we only use the 2010 data covering 2,205 households.

5.1 Lottery and risk aversion measures

To construct a measure of risk aversion, we use two hypothetical[15] questions included in the VARHS to elicit individual's risk attitudes: "Consider an imaginary situation where you are given the chance of entering a state-run lottery where only 10 people can enter and 1 person will win the prize. How much would you be willing to pay for a 1 in 10 chance of winning a prize of 2,000,000 Vietnamese Dongs (VND)?" and "How much would you be willing to pay for a 1 in 10 chance of winning a prize of 20,000,000 VND"?[16]

[INSERT TABLE 1 ABOUT HERE]

The lottery questions were submitted to the entire sample of household heads, but only around 37% of respondents answered as being willing to purchase the lottery. Out of 1,386 others, about 14% did not answer and 48% refused to pay a positive price. High non-responses and zero-answers rates were also found in Hartog et al. (2002) and Guiso and Paiella (2008) in similar lottery questions. There are two possible explanations for this pattern. First, some people may consider gambling as morally objectionable. The perception of gambling may be shaped by legal, sociological and ethical considerations. In Vietnam, except for the state-run lottery and a few five-star resorts running low

[15] Some concerns can emerge as it is believed that subjects should perform better if they earn some money for their actions. However, Camerer and Hogarth (1999) found that the presence and amount of financial incentives do not seem to affect average performance in many tasks. In particular, they found that increased incentives do not change average behavior in risky gambles substantively. This suggests that intrinsic motivation is still sufficient to perform well in hypothetical lottery tasks.

[16] These values are equivalent to US$100 and US$ 1,000, respectively. Whereas winning the first prize would imply on average an increase of around 5% in household wealth, the second prize would raise wealth in about 50%. Thus, it is probably that the set of incentives differs between lotteries, although a correlation is expected. The second lottery represents a relatively large risk. We consider this as robustness check because expected utility maximizers behave as risk-neutral individuals with respect to small risks even if they are averse to larger risks (Arrow, 1970). Thus, we expect that the larger lottery prize is a better strategy for eliciting risk attitudes when relying on expected utility.

profile casinos for foreigners only, gambling of any kind is illegal.[17] This makes it harder to distinguish the zero-answers that truly reflect strong risk aversion from those that reflect the usual variety of reasons for not answering. Second, a higher non-response rate was likely due to the complexity of the question, which might have required long time to understand and provide a sensible answer. Furthermore, lottery questions were introduced abruptly by the interviewers as part of a broader survey, without any set of introductory questions. The latter may have also led many respondents to skip this question. However, this strategy may have its advantages. First, asking questions abruptly would avoid that the way how introductory questions are framed distort the answers and therefore the elicitation of the true preference parameter. Second, the strategy with no "warm up" questions may have effectively discarded respondents with a poor understanding of the question, avoiding bringing in noisy answers (Guiso and Paiella, 2008).

[INSERT FIGURE 1 ABOUT HERE]

Figure 1 shows the distribution of the willingness to pay for non-zero answers. The reported price ranges from 1,000 to 2,000,000 and 10,000,000 for the lottery with a small and big prize, respectively (5.5% of respondents offered more than 2,000,000 in the small prize lottery. We omit these responses because such a price leads to a sure loss). For the small price lottery, the bulk of the responses are from 1,000 up to 200,000. In the big prize lottery, the distribution is more dispersed; around 80% of values are between 1,000 and 1,000,000. In both cases, the median is substantially smaller than the mean, signaling distribution with a long right tail.

These prices can be considered as reservation prices above which households would reject the lottery. We use them to compute formal measures of absolute risk aversion by applying Expected Utility (EU) theory as in Hartog et al. (2002) and Dang (2012).[18] Alternatively, we characterize attitudes toward risk qualitatively. We denote risk averse farmers with a dummy variable taking the value of 1 if farmers report a price lower than the expected gain offered by the lottery; risk neutral if this price is equal to the expected gain; and risk lover if the price is higher than the expected gain. Descriptive statistics are shown in Table 1. Among the individuals willing to purchase the lottery,

[17] Around 68% of respondents in the 2012 VARHS state that gambling is a severe problem in their communities.

[18] EU implies that the utility of wealth W, without participation in a lottery with a winning price Z and probability α , is equal to expected utility when participating at reservation price λ: $U(W) = (1-\alpha)U(W-\lambda) + \alpha U(W+Z-\lambda)$. By applying a second order Taylor expansion of the right hand side around $U(W)$, we have: $U(W) = U(W) + \alpha Z U'(W) - \lambda U'(W) + U''(W)((1-\alpha)\lambda^2 + \alpha(Z-\lambda)^2)/2$. After rearranging, we yield the Arrow-Pratt-measure of absolute risk aversion as: $A(W) = -\frac{U''(W)}{U'(W)} = \frac{\alpha Z - \lambda}{0.5\lambda^2 + 0.5\alpha Z^2 - \alpha\lambda Z}$.

the great majority (81% in the small and 86% in big prize lottery) is risk averse; around 6% are risk neutral; and 7-8% risk lovers. A high degree of risk aversion among Vietnamese farmers has been reported in the literature before. For instance, Nielsen et al. (2013) find substantial risk aversion under different risk preference elicitation methods among a sample of 300 rural households in northern Vietnam. The authors classify 84% of the respondents as risk averse, with 52% being very risk averse. Similar levels of risk aversion were also found in Tanaka et al. (2010). Strong risk aversion among Vietnamese farmers is not surprising; given the substantial risk they have to face, i.e. natural disasters, crop and livestock diseases, illness, etc., and the lack of adequate formal insurance mechanisms and limited government assistance to deal with shocks (Nielsen et al., 2013).

5.2 Production, household and weather shock data

We use data on the total value of pesticides per square meter applied in rice production as dependent variable in equation (1).[19] In this model, we control for the following socioeconomic and farm level characteristics: a dummy to denote the gender of household head taking the value of one if the farmer is male; household head's age in number of years; schooling measured by the number of years of formal education (actual and squared values); farm size measured in total land in square meters; number of household members; a dummy denoting if at least one family member received pest extension services the last twelve months; total household wealth constructed using fixed asset values (livestock, equipment and machinery), liquid asset values (savings, crop stores), and all consumer durables; total household incomes including wages, incomes gained from agricultural and off-farm activities, sales of assets, etc.; a dummy variable indicating whether households received transfers from government and/or family members/relatives (public/private sources); and geographical characteristics such as land terrain and soil quality that may condition the negative effects of shocks on agricultural activities.[20]

[19] By simply summing the value of all pesticides, we are ignoring the fact that different substances have different levels of toxicity and degradability. A better measure that accounts for this heterogeneity should consider a higher weight to highly toxic and persistent pesticide. For example, epidemiological studies have linked the adverse effect observed on human and animal health with the use of certain classes of pesticides: carbamates, organophosphates and pyrethroids. Unfortunately, information on type, chemical class, name and therefore toxicity of pesticides are not available in the survey.

[20] We proxy land terrain and soil quality using self-reported information by household heads in the VARSH survey. Land terrain is constructed using household heads' answers on the topography of their plot: "In general, what is the slope of this plot? Flat, slight slope, moderate slope or steep slope?". This variable ranges from 1 (flat terrain) to 4 (steep slope). We define a dummy variable to proxy for land terrain, which takes the value of 1 if the average across plots is less than 2, meaning that household's plots are on average flat. Soil quality is measured by household heads' answers on land fertility of their plot: "Compared to the average land fertility in the village, is the quality of this plot: less than the average, average, or better than the average? This variable ranges from 1 (less than the average) to 3 (better than the average). To compute a household level indicator of soil quality, we define a dummy variable which takes the value of 1 if soil quality of plots is average or better than the average. Additionally, we include dummies for North, Central and South Vietnam.

In order to estimate equation (2), we use the quantities and values of inputs and outputs used in rice production. Total output of farms consists of kilos of rice per square meter. The inputs include labor, seeds, fertilizers, pesticides, irrigation and the use of improved seeds. Labor is expressed in total number of days per square meter; seeds include total value of seed applied per square meter; fertilizer is measured by total value of fertilizers per square meter; pesticide use intensity is proxied by total value of pesticides per square meter; irrigation consists of a dummy variable that take the value of one if the farm uses any no-manual irrigation system, zero otherwise; improved seed is a dummy variable indicating if the farmer uses this technology, zero otherwise; and proxies for land terrain and soil quality.

Finally, information on shocks is obtained by directly asking households to report whether or not they suffered any shock from a predetermined list. Then, they are requested to rank the shocks in order of importance and to provide an estimation of the monetary loss in terms of Vietnamese Dong (VND). Thus, the data allows us to disaggregate overall shocks into two groups of interest: pest and drought shocks. We assume that the occurrence of pest shocks would reflect a bad state of nature regarding pest infestation. Furthermore, the incidence of past droughts as a proxy for water availability may be a good indicator of a bad state of nature in other crop growing conditions.

Descriptive statistics of the set of controls, production and shocks variables used in the analysis are shown in Table 2.

[INSERT TABLE 2 ABOUT HERE]

From the Table we see that total rice production was lower in 2010 than other in 2008 and 2012 (CIEM et al., 2011; 2013). A higher incidence of natural shocks may have led farmers to crop failure, and then to the poorer yields observed in 2010. In this context, our data reveals that around 31 percent of households experienced a pest shock between 2009 and 2010 with an average monetary loss of 1,107 (000 VND), representing 8% decrease in household income per capita. Although pest shocks are more prevalent, drought events are also important. Our data show that 13% of households reported to have been affected by a drought between 2009 and 2010. Average monetary losses after the incidence of a drought, on average, amounted to 300.000 VND, representing 2% decrease in household income per capita.

6 Results

6.1 The effect of risk aversion on pesticide use

Table 3 reports results for the pesticide input demand estimation (equation 1). Columns 1-3 show the estimated coefficients for the total sample with risk aversion measures calculated with responses to the small prize lottery.[21] While columns 1-2 include measures of absolute risk aversion, column 3 considers a dummy variable for risk averse farmers. Column 1 includes dummies for shock events; column 2 incorporates monetary losses instead of dummy indicators. The remaining columns report the results as computing risk aversion measures with answers to the big prize lottery.

[INSERT TABLE 3 ABOUT HERE]

Regarding the control variables, we find that training in pest management is negatively and significantly associated with pesticide use. The latter could be the result of the expansion of IPM and training programs in Vietnam. In addition, we find that wealth, income and access to credit are key determinants of pesticide use, which would indicate that budget constraints remain important for pesticide demand. Further, households with more family labor use less pesticide. The negative association could indicate that households substitute pesticides for family labor, when the adoption of pest management practices (such as manual weeding) is labor intensive. Moreover, the coefficient on farm size is positive and significant, which indicates additional evidence of the importance of budget constraints. Furthermore, pesticides are used more intensively in better plots (flat terrain and good soil). Better agro-ecological conditions imply higher yields and therefore more crop to protect in case of a severe pest. Finally, human capital characteristics such as a producer’s age and education are found to be significant determinants of pesticide use. Older farmers using more pesticide may reflect reluctance of older people to switch to potentially more unknown pesticide less-intensive practices. Education is also positively associated with pesticide use. This result contradicts previous finding (Liu and Huang, 2013). However, the positive association may be related to the fact that education eases saving and access to credit (Knight et al, 2003).

We are interested in examining the risk property of pesticide use. We find that our measure of risk aversion is significant and negative, indicating that risk averse farmers apply on average less

[21] Columns 1-3 in Table 3 report a smaller number of observations because we omit those responses with willingness to pay greater than 2.000.000 VND.

pesticides. This result remains robust to the use of different lottery prizes, quantitative and qualitative risk aversion measures,[22] the inclusion of farm and socioeconomic characteristics, and shocks variables as controls. This finding would suggest evidence in favor of pesticide being a risk-increasing input, and an indication that multiple risks are important when analyzing production input decisions in rural Vietnam.

To explore it further, we focus our attention on the effect of pest and drought shocks on pesticide input use. We note that the occurrence of pest shocks does not enter significantly in any of the specifications in Table 3. In contrast, drought events are clearly associated with a reduction in pesticide use. This would suggest that farmers care about general growing conditions, and farmers find it optimal to reduce the amount of pesticides in water shortage periods due to reduction in production volumes. These results are robust to the use of monetary measures of shocks.

6.2 The effect of pesticide input on production risk

Table 4 reports results from estimating the mean function (equation 2) and the variance function (equation 3). Column 1 shows estimated coefficients for the mean function[23] by NLS and column 2 presents estimations of variance production function by OLS.

[INSERT TABLE 4 ABOUT HERE]

Traditional inputs have positive marginal effects, consistent with theory. In the damage-production function, we assume that irrigation, improved seeds and pesticides are control inputs so that they do not affect yield directly but only indirectly through impacts on potential outputs. The parameters of irrigation and pesticide input in the abatement damage function are positive and significant, highlighting the role that these inputs play in controlling potential crop damage coming from water stress and pest infestation, respectively.

Results for the variance function shed some light on the risk property of inputs. Overall, estimates suggest that chemical fertilizers, improved seeds and irrigation reduce yield variability and hence production risk. The finding on irrigation is in line with the argument that farmers maintain

[22] In addition to the Arrow-Prat and qualitative measures of risk aversion, we also used the values of willingness to pay in our regressions. Results point to the same directions; farmers with smaller willingness to pay use less pesticide.

[23] We calculated the Breusch Pagan test to evaluate the null hypothesis of homoscedasticity against alternative hypotheses of heteroskedasticity. The Breusch-Pagan LM statistic is 378.93, strongly rejecting the null hypothesis. The latter supports the multiplicative heteroskedastic model and suggests that the Just and Pope specification is an appropriate framework for the analysis of the risk effect of pesticide in Vietnam.

irrigation as a way of insurance against potential yield losses from water stress. The key role that irrigation plays to reduce production fluctuations confirm the importance of supplying a stable and continuous flow of hydric resources in rice production. In contrast, the positive marginal effect on seeds and pesticides suggests that these inputs are risk-increasing. Note in particular, that the positive marginal risk of pesticides is in line with risk averse farmers using less amount of pesticides (shown in section 6.1), suggesting consistency across experimental and econometric methods.

6.3 Why is pesticide risk-increasing in Vietnam?

In the previous sections we documented that the risk-increasing characteristic of pesticide use is not dependent on chosen methodology. What then is the main source of the risk effect of pesticides? Following Horowitz and Lichtenberg (1994), the risk-increasing property of pesticides is more likely to arise in settings in which uncertainty regarding other growing conditions, i.e. rainfall, is relatively more important than pest infestation. To explore this further, we expand the mean function specification and include interactions of our proxies for the state of nature regarding pest and rainfall with pesticide use. Thus, we compare marginal productivities of using pesticide during the incidence of pest and rainfall shocks. As using the damage function specification with additive error, the NLS estimator fails to converge. We therefore assume a quadratic functional form to ease convergence. Results are showed in Table 5. We interact pesticide inputs with shocks indicators in columns 1; in column 2 we replace the drought indicator with monetary losses. We find that productivity of using pesticide is not statistically different from zero when farmers are affected by pest. This result remains when using measures of pest losses. In other words, marginal damage reduction does not seem to be higher during less favorable growing conditions, such as periods of high pest density or when pests are more damaging, suggesting an unclear risk-reducing effect of pesticides. In contrast, we find that pesticide productivity is lower during drought periods (column 1), suggesting a risk-increasing effect of pesticides. The latter indicates on aggregate that the risk-increasing effects of pesticide use may be larger than its risk-reducing effect.

Although both pest and drought risk are both important sources of uncertainty in agricultural production in Vietnam, farmers seem to react more to adverse drought related events as compared to pest related shocks. This could signal that farmers either have better knowledge of pest incidence probabilities and adjust optimal behavior accordingly (pests are internalized), or that application of pesticides continuously are implemented at high probability pest levels (leading on average to inefficient overuse of pesticides) independent of realized pest shocks. Our results suggest that it is the latter mechanism that dominates in the case of Vietnamese farmers, potentially with detrimental consequences for the future.

7 Robustness

7.1 Non-responses and zero price observations

One concern with the analysis is non-response bias or "zero responses". We therefore estimate the pesticide use equation excluding these observations. However, significant differences between farmers willing to participate in the lottery and those who were not can make the exclusion of non-participants problematic. To explore these divergences, Table A1 presents mean difference tests for the balancing properties between participants and non-participants in the lottery. Results confirm differences between the two groups. We therefore apply the inverse probability weights (IPW) to account for a potential bias when excluding zero and non-response observations. Results are shown in columns 1-4 of Table A2. We conclude that the exclusion of zero-price answers and non-respondents do not change results fundamentally.

7.2 Risk aversion and other inputs

An additional concern with the lottery approach is that a negative association of the risk aversion measure with pesticide use may be reflecting general aversion to investment rather than something particular to pesticide use. Put differently, risk averse farmers may use less amount of pesticides because they are not willing to incur additional risk, and if so, results may not be attributable to the fact that pesticide is risk-increasing. To address this, we explore the association between risk aversion and fertilizer use, an input that involves even larger investments (see Table 2). If results are driven by general aversion to investment, then we should find that more risk averse farmers also use fewer quantities of fertilizer. Results are shown in Table A2, columns 7 and 8, showing that risk aversion increases the use of fertilizer input. This result is therefore consistent with fertilizer use reducing production variance, and thereby being labelled as a risk-decreasing input. Thus, we conclude that our risk aversion measure is not reflecting overall aversion to investment.

7.3 Self-reported data

A further concern with our definition of drought shocks is that it relies on self-reported data. That may raise a systematic reporting bias since weather shocks data may not be a function of geographical location. Alternatively, we use calculations of the Standardized Precipitation Index (SPI) by the National Centre for Environmental Predictions (NOAA) (McKee, et al., 1993; 1995) to identify dry cycles. Specifically, we use a 9-month time scale index constructed on 0.5° lat/lon grid monthly precipitations of 1949-2014 over the main rice growing season in Vietnam (October-June).[24] Due to the absence of information on households' locations, we extrapolate this information at the district level. The SPI index is a continuous indicator that ranges from negative to positive values. Thus, larger values indicate a better state of nature with regard to rainfall. Statistics of the SPI confirms a dry cycle in 2010. In this year, the SPI ranged from -2.38 to -0.5 with a mean of -1.43, suggesting a dry agricultural season, mainly in northern and central Vietnam (see Figure A1). Results are presented in columns 5 and 6 of Table A2, and are qualitatively the same as reported in the main specifications. Farmers apply larger quantities of pesticide in periods with higher rainfall, and the inclusion of a rainfall-based drought index does not affect conclusions regarding our risk aversion measures.[25]

7.4 Specification and unobserved characteristics

A concern with the production function estimates is that they are likely to be specification dependent. As robustness check, we re-estimate the mean function for quadratic and Cobb-Douglas specifications. Furthermore, we also estimate the JP production function using panel data for 2010 and 2012. Descriptive statistics for the panel are shown in Table A3. Here, risk marginal effects of input are identified by using the variance that farmers experience within their own farms. We assume a linear quadratic functional specification for the mean function in this case. An advantage of this specification is that the farm-specific effect is additive, which is a requirement for the JP model (Eggert and Tveteras, 2004; Gardebroek et al. 2010). Results are presented in Table A4 and A5. As before, traditional inputs have positive marginal effects, consistent with theory. The quadratic term is negative and significant for all inputs, excepting pesticides, suggesting some evidence of decreasing marginal returns. The risk-increasing property of pesticides is also robust in

[24] A drought occurs if the SPI value falls at or below minus 1.0. Similarly, wet periods are identified with values equal or greater than 1.0. A value between -1 and 1 indicates no climatic anomaly.

[25] Findings on pesticide productivity being higher during better growing conditions measured by the SPI index remains robust to the use of panel data, suggesting a more likely risk-increasing effect of pesticides (see Table A5).

FE specification, and interestingly the FE estimates for the mean function show a U-inverted shape relation between pesticides and yield, suggesting a threshold from which pesticides start becoming effective in enhancing yields. Estimates of the variance function using a Cobb-Douglas specification gives similar conclusions. In fact, pesticide use is the only input that is consistently found to be risk-increasing throughout all specifications.

8 Conclusions

The excessive and unsustainable use of pesticide has created concerns because of its detrimental effects on farmers' health, the environment and agricultural sustainability. Thus, the overuse of chemical pesticide remains an important development issue, and understanding pesticide input decisions is a key requisite to sound policy-making. This paper examines the risk effects of pesticide use by using a lottery in combination with a production function approach on the same dataset of rice farmers in Vietnam. We also investigate the sources of the risk effects of pesticides.

Results from the lottery approach indicated that risk averse farmers are more likely to use fewer quantities of pesticide. Findings from the production function approach showed that pesticides increase production risk. Thus, both approaches consistently give evidence in the same direction, supporting the hypothesis of pesticide use being a risk-increasing input. The latter discards any incidence of the approach in determining the risk property of inputs.

We also found that the reduction in pesticide productivity in drought periods may be significant and that it may offset potential higher benefits from damage reduction when pest is high, suggesting that the risk-increasing effect of pesticides may dominate. This is consistent with pesticide use being a risk-increasing input, as pest damage may not be independent of rainfall; pesticide productivity will then be lower during drought periods since pesticide use is not dynamically optimally adjusted to the lower yields. These findings were found to be robust to alternative definitions of risk aversion and weather shocks, the use of different functional forms and panel data, and the exclusion of non-lottery participation observations. In addition, we noted that our results are not driven by general aversion to investment.

However, one additional caveat deserves attention. Our results may be crop-specific since trade-offs between pest and drought risk are supposed to vary across different cropping activities. For example, maize is relatively more resistant to water stress than rice and therefore pesticides may be more likely to be risk-decreasing in maize production. However, focusing on rice has some advantages. Rice is the major crop in Vietnam and is typically grown by most rural households (CIEM, et al., 2011; 2013). This characteristic reduces concerns that our results can be confounded by selection into rice production.

Despite these considerations, our findings have important implications for the success of government interventions to address concerns of the excessive use of pesticides. For an instrument aimed at reducing a pollutant input to work, it is necessary to understand the risk character of this input. If it is found that the input is risk-decreasing/increasing, then risk management instruments are quite likely to substitute/complement the inputs in the production process (Rossen and Hennessy, 2003; Schoengold et al. 2014). For example, crop insurance has been proposed as an instrument for reducing pesticides, arguing that it provides a substitute for the risk management benefits of pesticides (Babcock and Hennesey, 1996; and Smith and Goodwin, 1996). Based on the evidence that pesticides are positively correlated with production risk, crop insurance may instead exacerbate a pollution problem. Even with moral hazard, which reduces the use of all inputs, the high level of risk aversion among Vietnamese farmers would still lead to the observed risk effects (Ramaswami, 1993). This suggests that policies promoting more sustainable agricultural practices such as the Integrated Pest Management (IPM), and communicational programs addressed to increasing farmers’ awareness of pesticide risk may display advantages over other risk management instruments.

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Tables

Table 1. Descriptive statistics for lottery answers and risk attitudes. 2010.

Variables	Small prize lottery		Big prize lottery	
	Mean	Dev	Mean	Dev
Categories				
Non response	14.2		14.0	
Zero price	48.7		48.5	
Positive price	37.1		37.5	
Total	100		100	
Risk categories				
Risk averse	81.0		86.1	
Risk neutral	5.6		6.3	
Risk loving	7.9		7.6	
Inconsistent	5.5		0.0	
Total	100		100	
Absolute risk aversion	0.59	0.69	0.07	0.06

Note: Risk categories are defined among observations with positive willingness to pay.

Table 2. Household, production and shock variables. 2010.

Variables	Mean	St dev	Min	Max
Household characteristics				
1= HH is male	0.86	0.35	0	1
Head's age (years)	49.24	12.92	14	91
Head's schooling (N grades)	5.66	3.84	0	12
Farm size (m2)	8,600	11,372	0	138,500
# family members	4.87	1.91	1	15
1= HH received pest extension	0.35	0.48	0	1
1= HH borrowed money	0.53	0.50	0	1
Household's incomes (000 VND)	66,555	87,189	0	2,076,720
Household's wealth (000 VND)	40,962	49,796	0	814,600
1 = HH received public-private	0.86	0.35	0	1
Output and input variables				
Output (kg)	1,747	4,095	0	116,400
Land (sqr meter)	4,503	7,513	50	118,000
Labor (days)	106	75.84	0	650
Seed value (000 VND)	844	1,918	0	48,000
Fertilizer (000 VND)	2,366	7,750	0	250,000
Pesticide (000 VND)	1,057	6,565	0	250,000
Yield (kilos/sqr meter)	0.42	0.16	0	2.0
1 = farmers irrigate	0.86	0.35	0	1.0
1 = farmer use improved seed	0.75	0.43	0	1.0
Labor per sqr meter (days/sqr meter)	0.04	0.03	0	0.3
Seed per sq meter (000 VND/sqr meter)	0.24	0.24	0	6.9
Fertilizer per sq meter (000 VND/sqr meter)	0.59	0.62	0	10.0
Pesticide per sqr meter (000 VND/sqr meter)	0.15	0.21	0	2.7
1 = Good soil quality	0.77	0.42	0	1
1= Flat land terrain	0.66	0.48	0	1
Shock variables				
1= farmers was hit by a pest shock	0.31	0.46	0	1
1= farmers was hit by a drought shock	0.13	0.33	0	1
Loss after a pest shock (000 VND)	1,107	4,384	0	126,600
Loss after a drought shock (000 VND)	300	1,747	0	41,000
Observations		2,205		

Note: Own elaboration based on dataset.

Table 3. Estimates of the Tobit model for the logarithm of pesticide value per square meter. Total sample.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Risk aversion						
Absolute risk aversion (small prize)	-0.025***	-0.023**				
	(0.009)	(0.009)				
Absolute risk aversion (big prize)				-0.247**	-0.246**	
				(0.104)	(0.104)	
1= Risk averse (small prize)			-0.019			
			(0.016)			
1= Risk averse (big prize)						-0.045**
						(0.019)
Shocks						
1= farmers experienced a pest	0.002		0.003	0.003		0.002
	(0.006)		(0.006)	(0.007)		(0.007)
1= farmers experienced a drought	-0.016**		-0.016**	-0.019**		-0.019**
	(0.008)		(0.008)	(0.008)		(0.008)
Monetary loss						
Ln(Loss after a pest shock)		0.001			0.001	
		(0.001)			(0.001)	
Ln(Loss after a drought shock)		-0.003**			-0.003***	
		(0.001)			(0.001)	
Control variables						
1= HH is male	-0.002	-0.001	-0.001	0.000	0.001	0.007
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Ln(Head's age)	0.030**	0.023**	0.029**	0.034***	0.034***	0.035***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Ln(Head's schooling)	0.028**	0.024**	0.028**	0.026**	0.026**	0.025**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Ln(Head's schooling)^2	-0.006	-0.005	-0.006	-0.005	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ln(farm size)	-0.010***	-0.005	-0.011***	-0.011***	-0.011***	-0.011***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Ln(# family members)	-0.030***	-0.027***	-0.030***	-0.033***	-0.033***	-0.032***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
1= HH received pest extension	-0.013**	-0.008	-0.014**	-0.012*	-0.011*	-0.010
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
1= HH borrowed money	0.013**	0.014***	0.013**	0.015***	0.015***	0.015***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ln(Household's wage)	0.012***	0.011***	0.013***	0.012***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Ln(Household's wealth)	0.00286***	0.003***	0.003**	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
1 = HH received public- transfers	0.002	0.004	0.000	-0.004	-0.004	-0.003
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
1 = Good soil quality	0.013**	0.016***	0.012*	0.011*	0.011*	0.012*
	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)
1= Flat land terrain	0.035***	0.028***	0.035***	0.034***	0.034***	0.0345***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	0.065	0.091	0.070	0.059	0.059	0.079
	(0.065)	(0.064)	(0.066)	(0.066)	(0.066)	(0.067)
Zone dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,156	2,156	2,156	2,205	2,205	2,205

Note: Columns (1)-(3) display the estimated coefficients for the total sample using responses to the small lottery prize. Columns (4)-(6) use answers to the big lottery prize. The dependent variable is the logarithm of the pesticide value per square meter used in rice production. All specifications are estimated by the Tobit model and include a full set of control covariates. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 4. Estimation of mean and variance functions.

Variables	(1) Mean	(2) Variance
Inputs		
1= farmers irrigate		-0.042***
		(0.006)
1 = farmer use improved seed		-0.011**
		(0.005)
Labor per sq meter	0.069***	-0.033
	(0.013)	(0.087)
Seed value sq meter	0.043***	0.049***
	(0.013)	(0.015)
Fertilizer value per sq meter	0.101***	-0.089***
	(0.009)	(0.009)
Pesticide value sq meter		0.112***
		(0.017)
1 = Good soil quality	0.054***	0.0005
	(0.015)	(0.0046)
1= Flat land terrain	0.086***	-0.001
	(0.017)	(0.005)
Damage control inputs		
μ	-0.821***	
	(0.228)	
Pesticide value sq meter	7.132**	
	(2.896)	
1= farmers irrigate	1.125***	
	(0.247)	
1 = farmer use improved seed	-0.094	
	(0.185)	
Zones dummies	Yes	Yes
Constant	0.636***	0.164***
	(0.042)	(0.008)
R square	-	0.108
Observations	2,199	2,199

Note: Column (1) displays the estimated coefficients of the yield function. The dependent variable is kilos of rice per square meter. This specification is estimated by NLS. Column (2) shows the coefficients for the variance function. The dependent variable is the absolute value of predicted errors of the mean function. This specification is estimated by OLS. Robust standard errors in parentheses for the mean function.*** p<0.01, ** p<0.05, * p<0.1.

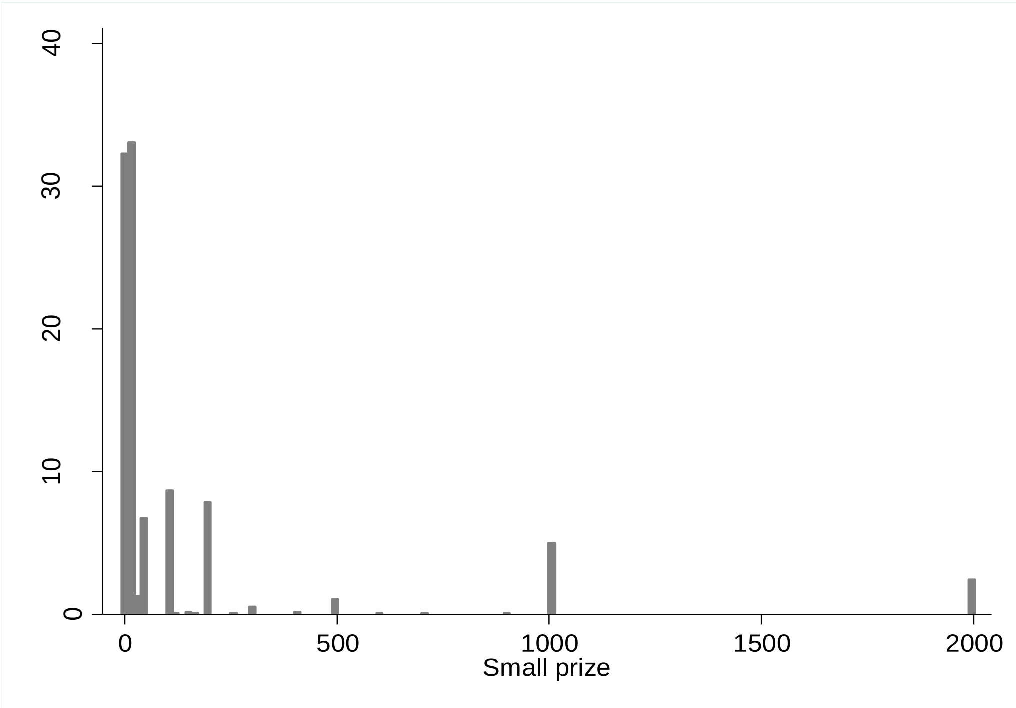
Table 5. Estimation of mean functions with interactions. Dependent variable: Yield.

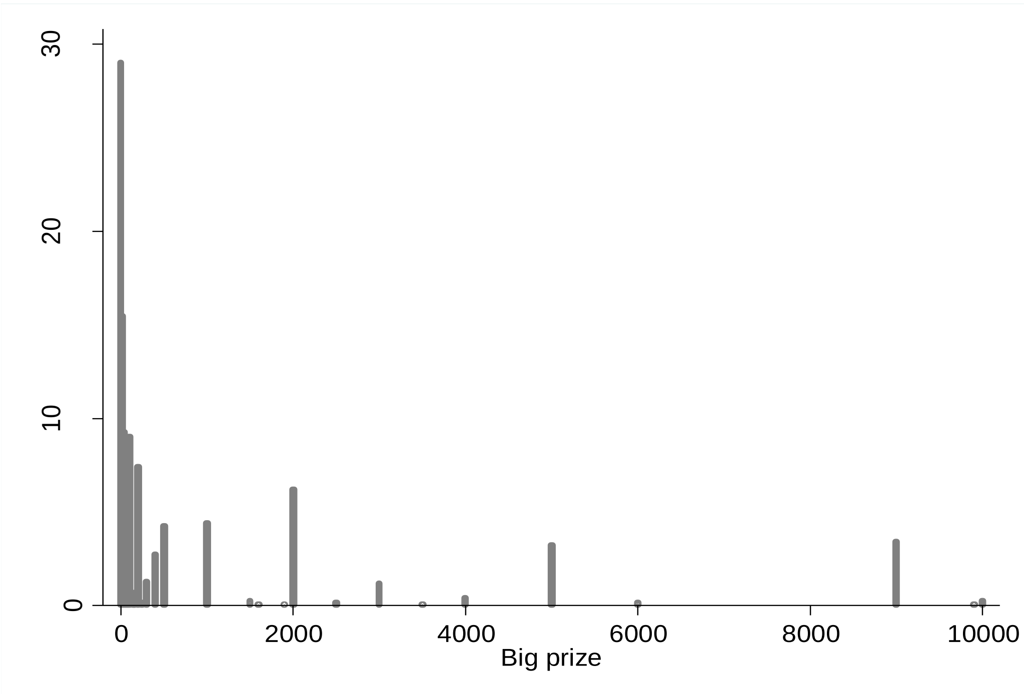
Variables	(1)	(2)
Inputs		
1= farmers irrigate	0.038***	0.038***
	(0.008)	(0.008)
1 = farmer use improved seed	0.008	0.004
	(0.007)	(0.007)
Labor per sq meter	2.527***	1.947***
	(0.322)	(0.332)
Labor per sq meter^2	-9.306***	-7.325***
	(2.261)	(2.152)
Seed value sq meter	0.153***	0.177***
	(0.0251)	(0.025)
See value per sq meter^2	-0.031**	-0.037***
	(0.006)	(0.007)
Fertilizer value per sq meter	0.075***	0.070***
	(0.010)	(0.009)
Fertilizer value per sq meter^2	-0.009***	-0.009***
	(0.002)	(0.002)
Pesticide value sq meter	0.132**	0.138***
	(0.052)	(0.050)
Pesticide value per sq meter^2	0.026	0.040
	(0.042)	(0.045)
1 = Good soil quality	0.010*	0.019***
	(0.006)	(0.006)
1= Flat land terrain	0.042***	0.026***
Shocks		
1= farmers experienced a pest	-0.019**	
	(0.008)	
1= farmers experienced a drought	-0.031***	
	(0.010)	
Ln(Loss after a pest shock)		0.000
		(0.000)
Ln(Loss after a drought shock)		-0.000**
		0.000
Pesticide*pest shock	0.065	
	(0.049)	
Pesticide*drought shock	-0.109*	
	(0.064)	
Pesticide*pest loss		0.000
		(0.000)
Pesticide*drought loss		0.000
		(0.000)
Zones dummies	Yes	Yes
Constant	0.192***	0.187***
	(0.015)	(0.014)
R square	0.415	0.436
Observations	2,199	2,199

Note: Column (1) displays the estimated coefficients of the augmented yield function as assuming interaction of pesticide input with shock indicators. Column (2) replaces drought indicators with monetary losses. The dependent variable is kilos of rice per square meter. Models are estimated by OLS, and include zone dummies. We use a quadratic functional form. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Figures

Figure 1. Histogram of the willing to pay for the hypothetical lottery. Positive willingness to pay (000 VND)





Source: Own elaboration based on dataset.

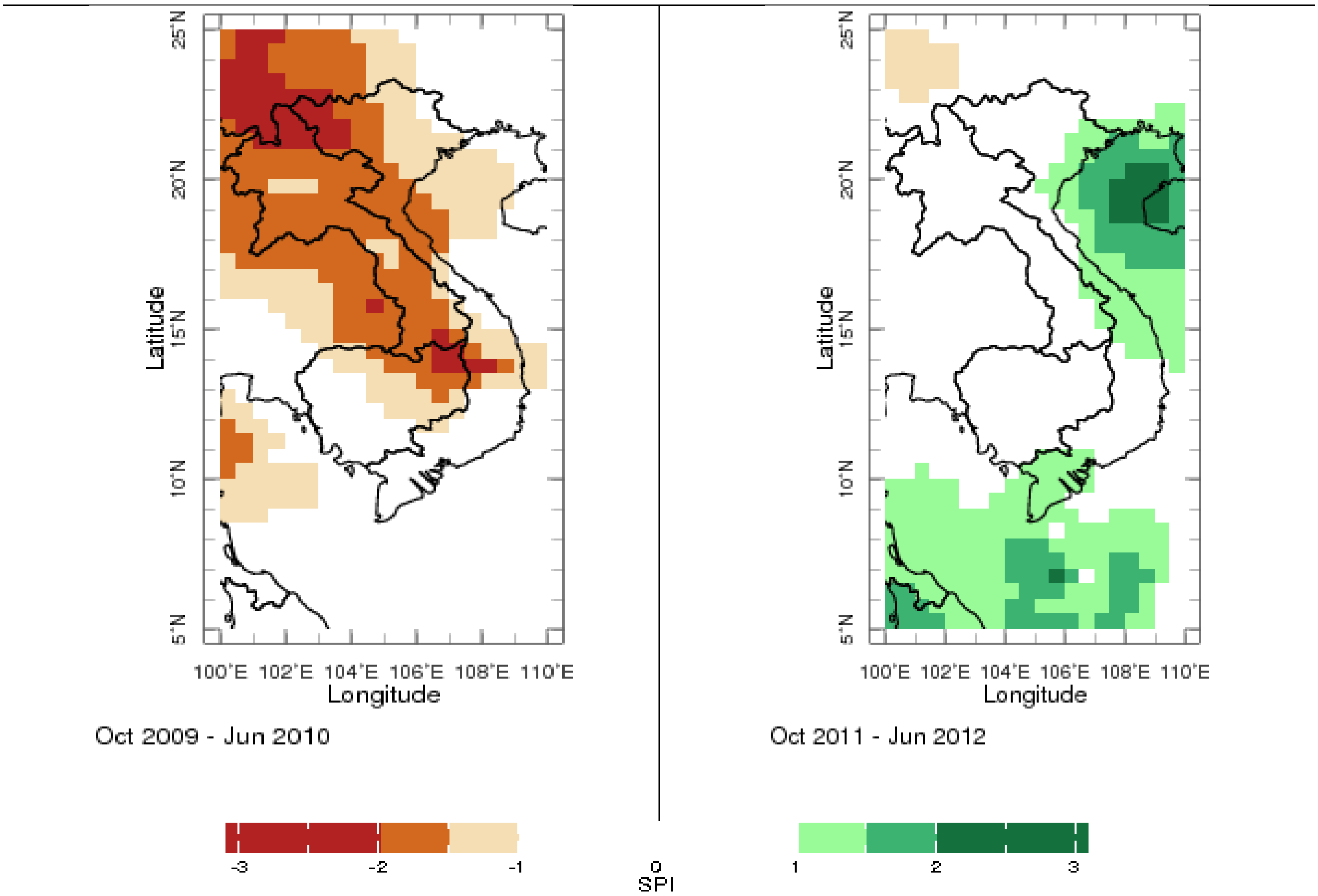
Appendix A: Additional Tables and Figures.

Table A1. Difference in means (participants vs. non-participants in the lottery)

Variables	Small prize lottery				Big prize lottery			
	Mean		Differences	p-value	Mean		Differences	p-value
	Non-part	Part			Non-part	Part		
1= HH is male	0.84	0.87	0.03	0.07*	0.84	0.88	0.03	0.03**
Head's age (years)	49.14	49.31	0.18	0.76	49.06	49.55	0.49	0.39
Head's schooling (N grades)	5.47	5.92	0.44	0.01***	5.47	5.97	0.50	0.00***
Farm size (m2)	8,973	7,973	-999.5	0.05**	9,017	7,901	-1,115	0.03**
# family members	4.92	4.78	-0.14	0.10*	4.94	4.76	-0.18	0.03**
1= HH received pest extension	0.37	0.32	-0.05	0.03**	0.37	0.32	-0.06	0.01***
1= HH borrowed money	0.52	0.53	0.01	0.69	0.52	0.54	0.01	0.53
Household's incomes (000 VND)	62,941	71,737	8,795	0.02**	63,105	72,348	9,243	0.02**
Household's wealth (000 VND)	39,279	43,083	3,804	0.09*	39,569	43,301	3,732	0.09*
1 = HH received public-private	0.80	0.75	-0.05	0.01***	0.80	0.75	-0.05	0.01***
1= farmers experienced a pest	0.33	0.27	-0.07	0.00	0.33	0.27	-0.06	0.00***
1= farmers experienced a drought	0.13	0.12	-0.02	0.23	0.13	0.12	-0.02	0.22
1 = Good soil quality	0.76	0.77	0.01	0.71	0.76	0.77	0.00	0.81
1= Flat land terrain	0.63	0.69	0.06	0.00***	0.63	0.70	0.07	0.00***
Observations	1,389	768			1,382	823		

Note: p<0.01, ** p<0.05, * p<0.1.

Figure A1. Spi index. 2010-2012.



Note: Red color identifies droughts (SPI lower than -1); while white color shows normal climate conditions (SPI between -1 and 1); and green areas identify wet periods (SPI greater than 1).

Table A2. Estimates of the Tobit model for the logarithm of pesticide/fertilizer value per square meter. Excluding non-participants (Weighted regression).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk aversion								
Absolute risk aversion (small prize)	-0.026***				-0.025**			
	(0.010)				(0.010)			
Absolute risk aversion (big prize)			-0.178*			-0.185*	0.402**	
			(0.107)			(0.110)	(0.183)	
1= Risk averse (small prize)		-0.014						
		(0.016)						
1= Risk averse (big prize)				-0.034*				0.083**
				(0.020)				(0.030)
Shocks								
1= farmers experienced a pest	-0.007	-0.005	-0.008	-0.009	-0.007	-0.008	0.001	0.004
	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.014)	(0.024)	(0.024)
1= farmers experienced a drought	-0.028*	-0.028*	-0.034**	-0.034**			0.024	0.024
	(0.015)	(0.015)	(0.015)	(0.014)			(0.029)	(0.029)
SPI index					0.066***	0.067***		
					(0.016)	(0.016)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographical variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zones dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.010	0.022	-0.017	-0.005	0.090	0.076	0.054	0.025
	(0.103)	(0.105)	(0.107)	(0.107)	(0.010)	(0.101)	(0.246)	(0.247)
Observations	768	768	819	819	768	819	819	819

Note: Columns (1)-(3) display the estimated coefficients for the sub-sample of non-zero respondents to the small lottery prize. Columns (4)-(6) use answers to the big lottery prize. The dependent variable is the logarithm of the pesticide value per square meter used in rice production. Columns (7)-(8) show the estimated coefficients for the logarithm of the fertilize value per square meter used in rice production All specifications are estimated by the Tobit model and include a full set of control covariates. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table A3. Production and shock variables. 2010-2012 panel.

Variables	2010				2012			
	Mean	**St dev**	**Min**	**Max**	**Mean**	**St dev**	**Min**	**Max**
Output and input variables								
Output (kg)	1,839	4,272	0.0	116,400	2,111	4,671	1.0	89,700
Land (sqr meter)	4,727	7,702	144	118,000	4,727	8,313	45.0	145,000
Labor (days)	109	77	0.0	650	108	87	0.0	1,000
Seed value (000 VND)	894	2,002	0.0	48,000	910	1,960	0.0	36,081
Fertilizer (000 VND)	2,496	8,148	0.0	250,000	2,319	6,264	0.0	144,401
Pesticide (000 VND)	1,147	6,942	0.0	250,000	1,048	6,621	0.0	216,597
Yield (kilos/sqr meter)	0.42	0.15	0.0	1.9	0.48	0.63	0.0	7.2
1 = farmers irrigate	0.85	0.35	0.0	1.0	0.88	0.32	0.0	1.0
1 = farmer use improved seed	0.74	0.44	0.0	1.0	0.76	0.43	0.0	1.0
Labor per sqr meter (days/sqr meter)	0.04	0.03	0.0	0.3	0.04	0.06	0.0	0.6
Seed per sq meter (000 VND/sqr meter)	0.24	0.25	0.0	6.9	0.25	0.33	0.0	3.4
Fertilizer per sq meter (000 VND/sqr meter)	0.59	0.60	0.0	10.0	0.62	0.64	0.0	12.1
Pesticide per sq meter (000 VND/sqr meter)	0.15	0.21	0.0	2.7	0.16	0.25	0.0	2.9
Shock variables								
1= farmers experienced a pest	0.31	0.46	0.0	1.0	0.30	0.46	0.0	1.0
1= farmers experienced a drought	0.13	0.34	0.0	1.0	0.09	0.28	0.0	1.0
Loss after a pest (000 VND)	1,133	4,539	0.0	126,600	1,302	5,321	0.0	138,994
Loss after a drought (000 VND)	301	1,773	0.0	41,000	91.04	637	0.0	13,745
Spi index	-1.43	0.60	-2.38	-0.5	0.50	0.55	-0.6	1.2
Observations	1,947				1,947			

Note: Own elaboration based on dataset. Figures correspond to the balanced panel. Values are deflated (2010=100).

Table A4. Estimation of mean and variance functions for alternative functional forms and panel data.

Variables	(1) Quadratic Mean	(2) Variance	(3) Cob Douglas Mean	(4) Variance	(5) Quadratic Mean (FE)	(6) Variance (FE)
Inputs						
1= farmers irrigate	0.039***	-0.003	0.119***	-0.030***	-0.006	-0.011
	(0.008)	(0.005)	(0.029)	(0.007)	(0.012)	(0.009)
1 = farmer use improved seed	0.007	-0.002	-0.001	-0.016***	0.024***	-0.000
	(0.007)	(0.003)	(0.022)	(0.005)	(0.009)	(0.005)
Labor per sq meter	2.493***	0.153**	0.067***	-0.063	-0.222	0.727***
	(0.322)	(0.067)	(0.013)	(0.097)	(0.380)	(0.091)
Labor per sq meter^2	-9.246***				9.979***	
	(2.243)				(1.671)	
Seed value sq meter	0.138***	-0.003	0.039***	0.048***	0.306***	0.047***
	(0.025)	(0.012)	(0.013)	(0.017)	(0.077)	(0.018)
See value per sq meter^2	-0.031***				-0.0811***	
	(0.007)				(0.029)	
Fertilizer value per sq meter	0.078***	-0.021***	0.092***	-0.074***	0.025	-0.003
	(0.010)	(0.007)	(0.010)	(0.010)	(0.027)	(0.011)
Fertilizer value per sq meter^2	-0.010***				0.006	
	(0.002)				(0.006)	
Pesticide value sq meter	0.137***	0.048***	0.054***	0.044**	-0.216*	0.081***
	(0.049)	(0.013)	(0.009)	(0.019)	(0.128)	(0.021)
Pesticide value per sq meter^2	0.042				0.312**	
	(0.049)				(0.146)	
Geographical variables	Yes	Yes	Yes	Yes	No	No
Zones dummies	Yes	Yes	Yes	Yes	No	No
Year variable	No	No	No	No	Yes	Yes
Constant	0.175***	0.094***	0.588***	0.176***	0.320***	0.061***
	(0.014)	(0.006)	(0.043)	(0.009)	(0.0294)	(0.010)
R square	0.403	0.039	-	0.076	0.372	0.074
Observations	2,199	2,199	2,199	2,199	3,894	3,894

Note: Column (1) displays the estimated coefficients of the yield function as assuming a quadratic functional form. This specification is estimated by OLS. Column (3) assumes a Cob-Douglas production function. The Cob-Douglas function is estimated by NLS. Finally, column (4) shows estimations using the panel 2010-2012 and assuming a quadratic function for the mean. This latter is estimated by FE and includes a dummy variable for the year 2012 (not shown). In these columns, the dependent variable is kilos of rice per square meter. Columns 2, 4 and 6 show the estimates of variance functions, respectively. The dependent variable is the absolute value of predicted errors. Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table A5. Estimation of mean functions with interactions. Fixed effect estimator (FE). Dependent variable: Yield.

Variables	(1)	(2)	(3)
Inputs			
1= farmers irrigate	-0.007	-0.007	-0.004
	(0.012)	(0.012)	(0.012)
1 = farmer use improved seed	0.022***	0.024***	0.019**
	(0.009)	(0.009)	(0.009)
Labor per sq meter	-0.268	-0.233	-0.202
	(0.365)	(0.374)	(0.369)
Labor per sq meter^2	10.14***	10.04***	9.786***
	(1.718)	(1.681)	(1.676)
Seed value sq meter	0.308***	0.305***	0.303***
	(0.078)	(0.077)	(0.074)
See value per sq meter^2	-0.0816***	-0.081***	-0.078***
	(0.031)	(0.030)	(0.029)
Fertilizer value per sq meter	0.025	0.025	0.028
	(0.028)	(0.027)	(0.028)
Fertilizer value per sq meter^2	0.006	0.006	0.006
	(0.006)	(0.006)	(0.006)
Pesticide value sq meter	-0.199*	-0.219*	-0.196
	(0.111)	(0.122)	(0.120)
Pesticide value per sq meter^2	0.310**	0.316**	0.285**
	(0.139)	(0.144)	(0.138)
1 = Good soil quality			
1= Flat land terrain			
Shocks			
1= farmers experienced a pest	-0.004	-0.007	
	(0.010)	(0.009)	
1= farmers experienced a drought	-0.054		
	(0.037)		
Spi index		-0.019	
		(0.013)	
Ln(Loss after a pest shock)			0.000
			(0.000)
Ln(Loss after a drought shock)			-0.000**
			(0.000)
Pesticide*pest shock	-0.092	-0.063	
	(0.087)	(0.080)	
Pesticide*drought shock	0.172		
	(0.348)		
Pesticide* Spi index		0.084*	
		(0.043)	
Pesticide*pest loss			-0.000
			(0.000)
Pesticide*drought loss			0.000
			(0.000)
Year variables	Yes	Yes	Yes
Constant	0.332***	0.323***	0.313***
	(0.029)	(0.028)	(0.0296)
R square	0.378	0.373	0.379
Observations	3,894	3,894	3,894

Note: Column (1) displays the estimated coefficients of the augmented yield function as assuming interaction of pesticide input with shock indicators. Column (2) replaces drought indicators with the SPI index; Column (3) incorporates monetary losses, instead. All the models are estimated by FE and include a dummy variable for the year 2012. We assume a quadratic functional form. In all the columns, the dependent variable is kilos of rice per square meter. Robust standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$.