European Journal of Operational Research 303 (2022) 1392–1402

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Innovative Applications of O.R.

Does risk management affect productivity of organic rice farmers in India? Evidence from a semiparametric production model[☆]

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ARTICLE INFO

Article history:
Received 28 March 2021
Accepted 28 March 2022
Available online 1 April 2022

JEL classification:
Q12
D22
D24
L24

Keywords:
OR in agriculture
Productivity
Production risk
Semiparametric model
Organic rice

ABSTRACT

This study analyzes the effects of farmers' risk on productivity where the production function is generalized to be specific to risk variables. This resulted in a semiparametric smooth-coefficient (SPSC) production function. The novelty of the SPSC approach is that it can explain the direct and indirect channels through which risk can affect productivity. The study uses several measures of risk, including attitudes toward risk, perceptions of risk, and risk management skills of farmers. It then shows how these risk-related variables affect productivity both directly and indirectly via the inputs. Using 2015 farm-level data from organic basmati rice (OBR) smallholders in India, the study finds that OBR farmers with high degrees of risk aversion had lower productivity than less risk-averse or risk-neutral OBR farmers. Additionally, OBR farmers who were most concerned about production risks (i.e., weather and pest risks) had higher productivity than their counterparts. Finally, the study reveals that OBR farmers can reduce production costs by increasing farm size.

1. Introduction

"*Productivity isn't everything, but in the long run it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker.*" Paul Krugman, The Age of Diminished Expectations (1997)

Although Krugman (1997) was referring to aggregate productivity, increasing productivity at the macro level requires increasing productivity at the micro (firm/farm) level, which is what we focus on in this paper. Productivity growth is usually defined as increase in output, holding the inputs constant. Thus, it has to come from factors other than the standard inputs in a production function.

Our focus in this paper is on agricultural production in which production risk plays an important role. Thus, we argue that one needs to take into account production risk in specifying and estimating productivity in a risky environment. Most earlier studies focusing on risk and productivity have used the production function as a tool of their analyses.[1] First proposed by Sandmo (1971) and refined by Just & Pope (1979), this formulation allows inputs to increase or decrease the variance of production or agricultural output. That is, riskiness is modelled in the variance of the error term in the production function. A weakness with this approach is that, since risk is defined in terms of the variance in production, it is measured ex-post. But risk is ex-ante (some-

☆ We would like to thank the Editor, Professor Mike Yearworth and three anonymous referees, whose comments substantially improved the paper.

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[1] Econometric studies within agriculture focusing on risk and using a conventional productivity framework include Just & Pope (1979), Griffiths & Anderson (1982), Antle (1983), Antle & Goodger (1984), Nelson & Preckel (1989), Wan & Anderson (1990), Kumbhakar (1993), Traxler, Falck-Zepeda, Ortiz-Monasterio R, & Sayre (1995), Regev, Gotsch, & Rieder (1997), Di Falco, Chavas, & Smale (2007), Serra, Zilberman, Goodwin, & Featherstone (2006), Serra, Zilberman, Gil, & Featherstone (2009), Shankar, Bennett, & Morse (2008), Tveteras, Flaten, & Lien (2011) and Mishra, Rezitis, & Tsionas (2019).

https://doi.org/10.1016/j.ejor.2022.03.051

thing that has not happened yet), and uncertainty about outcomes may well influence input choices and hence ex-post output. So the observed (actual) output depends on the producer's attitude towards risk, which affects input use decisions and therefore output/productivity. The Just-Pope type of production function formulation does not take producers' attitudes to risk into account, since the mean output is not affected by the degree of risk perceived by a producer. Thus, input productivities are not affected by risk perceptions, which is clearly not realistic.

Chambers & Quiggin (2000), drawing on the work of Arrow & Debreu (1954), introduced the state-contingent production function. In this framework, output is contingent on the state of nature that eventuates, given the inputs applied. This is not a property of the conventional production function, in which the role that inputs play remains the same regardless of which state occurs. The theory of state-contingent production function is well-established, but the empirical implementation of the state-contingent approach within agriculture is somewhat limited.[2] This is partly because of the lack of reliable and relevant state-dependent data.

There are several alternative ways, both to the Just and Pope framework and the state-contingent production function framework, to model how risk-related or Z variables (in our case risk attitude, risk perception and experience) affects productivity. One approach is to assume that the agents seek to maximize expected utility of profit in choosing levels of inputs and output. In this framework, one assumes a parametric profit function along with a production function to derive the input demand and output supply functions. This is what Ballivian & Sickles (1994) did when they estimated a system consisting of the input demand and output supply functions. That approach requires data on input and output prices, because the input demand and output supply functions depend on them. Without prices and variability in the price data, which is the case for our study, it is not possible to use this approach.

Another alternative way is to treat Z similar to X and write the production function as $Y = f(X, Z)$. An extension of that model is to let risk-indices (parametric functions of Z variables) enter as inputs in the production function ($Y = f(X, g(Z))$), as in Lien, Kumbhakar, & Hardaker (2017). But, a problem with both these approaches are that Z is different from X because it is not a standard input like X. Mathematically speaking, one cannot separate X from Z.

In this study we propose a framework in which risk changes the production technology. That is, $Y = f|_Z(X)$ where $f|_Z(.)$ indicates that the production function changes (shifts) with Z, thereby meaning that there is not a single production function for all level of Z. Note that this specification is different from $Y = f(X, Z)$ in which the technology is the same for all producers. That is, in a parametric function of $Y = f(X, Z)$ the parameters are the same for all producers, although outputs are different for different levels of Z and X. In contrast, in our specification $Y = f|_Z(X)$, the parameters are specific to the Z variables. For example, in a Cobb-Douglas (CD) specification of $Y = f|_Z(X)$, i.e., $Y_i = X_i'\beta$, the β parameters (the input elasticites) which define the technology are functions of Z. That is, $Y_i = X_i'\beta(Z)$. To make it more flexible we assume $\beta(Z)$ nonparametric. Note that in this CD specification Y and X variables are in log. This is labelled as the semiparametric smooth-coefficient (SPSC) regression model in which the parameters (both the intercept and the slope parameters) are nonparameric functions of Z. Thus, instead of modeling risk in the error variance (as in Just and Pope), risk in our framework affects mean output (and therefore profit as well as expected utility of profit).[3]

Based on the above discussion of alternative approaches, and the choice of a semiparametric production model, we set the following two objectives for this study. The first is to demonstrate a flexible semiparametric regression approach that directly includes risk-related aspects in a standard production function framework. The second is to gain insights of the effects on farm productivity of farmers' attitudes to, and perceptions of, risk, and of their risk management experience among producers of Organic Basmati Rice (OBR) in India. The influence on farm productivity of risk-related attributes could provide policy insights into the development of risk management programs, risk management decision-making and effective mechanisms of risk mitigation.

The remainder of the paper is divided into four sections. The modelling framework and estimation method are described in Section 2. The case of rice production in India and applied data are described in Section 3. Section 4 presents the results, and Section 5 provides concluding remarks and implications.

2. Modelling framework

2.1. The conceptual model

Compared with many of earlier studies, our study has a difference. We believe that the effects on farm production of adverse occurrences such as adverse weather events depend on how farmers prepare for and manage such risks. We hypothesize that what they do about potential adverse events will reflect their attitudes to risk (degrees of risk aversion), their beliefs about the chances and severity of such events, and their previous experience in preparing for and managing adverse events. Because of this, the Z or risk-related variables in our study do not actually represent 'risk' - defined as uncertain outcomes to which the decision-maker (DM) is not indifferent, nearly always with some outcomes entailing a loss for the DM. Because risk, as we conceive it, is essentially imaginary, existing only in the minds of decision makers, ex ante measures of risk per se are difficult if not impossible to formulate. Then, the Z variables included in our study (mainly) reflect the impacts on risky production of farmers' behavior and productivity. As noted in several studies (e.g., Boucher, Carter, & Guirkinger, 2008; Dercon & Christiaensen, 2011), the farmers' risk attitudes affect their risk management decision-making associated with production.

While using the semiparametric production function, risk attitude, risk perception and experience (Z) are considered as environmental inputs which affect output, but the impact may or may not be via the inputs X. One option then is to specify the production function as $Y = A(Z)f(X)$, where $A(Z)$ is a nonparametric function. When the risk-related variables (Z) are introduced in the intercept, they have a direct (neutral) impact on productivity, through a neutral shift in the production function. An extension is that Z can affect Y both neutrally and non-neutrally. That is, the productivities are affected by Z. We model this possibility by allowing the input coefficients to also be nonparametric functions of Z. We justify this by assuming that the production function is Z-specific, which makes the parameters functions of Z. With this extension, the Z variables are introduced both in the intercept and in the slope parameters of the production function. The intercept captures the direct effect of Z on Y. The slope parameters capture the effect on Y through the input elasticities, and we call them the indirect ef-

[2] The limited numbers of state-contingent production function studies in agriculture include O'Donnell, Chambers, & Quiggin (2010), Nauges, O'Donnell, & Quiggin (2011) and Hardaker & Lien (2014). Serra & Lansink (2014) and Serra, Chambers, & Lansink (2014) used a state-contingent framework for the generalized version of the Free Disposal Hull nonparametric estimator (DEA type) to model production uncertainty in Catalan arable farming.

[3] Baležentis & Sun (2020) used a semiparametric method in an analysis of technical inefficiency and total factor productivity growth among Lithuanian dairy farms.

fect. This indirect effect results in a non-neutral shift of the production function and influences the marginal effects of the inputs. Note that in this specification, the estimated relation between risk-related variables and input elasticities may not be interpreted as a causal relation.[4]

Compared to the standard textbook definition of the production function, our specification makes the production function more flexible, and the flexibility that we introduce can be econometrically tested. Further, in our study, the flexible semiparametric framework is different from the model used by Lien et al. (2017), where risk indices (parametric functions of risk-related variables) enter as inputs in the production (or distance) function (estimated with a nonlinear regression model). Ballivian & Sickles (1994) also analysed risk in farming in India. However, while they estimated a system of input demand and output supply functions parametrically, we estimated a production function with a flexible semi-parametric specification on the input coefficients. Ballivian & Sickles (1994) used profit maximization behavior to derive the input demand and output supply functions. In contrast, we do not use any behavioural assumptions. Thus, the modelling approaches are different. Further, while both the approaches treated risk aversion variable as inputs the Ballivian & Sickles (1994) approach requires data on input and output prices. Instead, we use the data on perceptions of risk and management skill variables in our model. Lastly, while Ballivian & Sickles (1994) used data from 1970s, our data is more recent (from 2015) and are collected from a survey from the farmers who produce only organic basmati rice.

2.2. Model specification

Studies using standard regression analyzes primarily use a linear model based on an assumption that the parameters are homogeneous among the farms or observations being investigated. That is, the technology is exactly the same for all farms. There are many ways by which one can extend this form of modelling to introduce technological heterogeneity. One option is to have a parametric structure (say log linear) in the standard inputs and allow for full heterogeneity of the parameters in the model (i.e., observation-specific parameters). The advantage of this formulation is that the parameters (which are functions of exogenous policy-relevant variables) have economic meaning (input elasticity). This is achieved with the SPSC formulation.[5] As stated in the introduction, in a CD model, this means $Y_i = X_i'\beta$, and the β parameters (the input elasticites) are nonparametric functions of Z. Thus, the CD SPSC model can be written as:

$$Y_i = \alpha(Z_i) + X_{1i}\beta_1(Z_i) + X_{2i}\beta_2(Z_i) + X_{3i}\beta_3(Z_i) + u_i, i = 1, \cdots, n, \tag{1}$$

where Y_i is the logarithm (log) of output (gross revenue) for farm i, X_{1i} is the log of land input, X_{2i} is the log of labor input, X_{3i} is the log of materials (materials), and Z_i is a vector of risk-related variables. In our empirical model we include three risk-related variables. These are: risk attitude (Z_1); perceptions of risk (Z_2); and risk management experience (Z_3). Finally, u_i is a random disturbance term, and the β parameters are smooth nonparametric functions to be estimated. Note that the model has a parametric structure in terms of the input variables. Such a model is very flexible because it allows the parameters to change with Z, making the parameters observation-specific if the Z variables are observation-specific. With this model, the overall marginal effect of the Z variables on output can be decomposed into a direct marginal effect and an indirect marginal effect. If all the β parameters are constants (i.e. $\beta_j(Z_i) = \beta_j, j = 1, \cdots, 3$), the model collapses to the partially linear model of Robinson (1988), where only the intercept, $\alpha(Z_i)$ is the nonparametric part of the model. On the other hand, if the β_j parameters, as well as the intercept, are linear functions of the Z variables, the model reduces to a restricted translog function (without the square and cross-products of the input and the Z variables). The model can comprise any parametric form of the $\beta_j(Z_i)$ and $\alpha(Z_i)$ functions, such as linear and quadratic (in log or in level). However, the main idea behind the SPSC model is not to assume any parametric form for them, although one can use any parametric form of the $\beta_j(Z_i)$ and $\alpha(Z_i)$.

In matrix form (1) can be written as:

$$Y_i = X_i'\delta(Z_i) + u_i \tag{2}$$

where $X_i' = (1, X_{1i}, X_{2i}, X_{3i})$ and $\delta(Z_i) = (\alpha(Z_i), \beta_1(Z_i), \beta_2(Z_i), \beta_3(Z_i))'$. This model can be estimated by employing the kernel method (Li et al., 2002). Pre-multiplying (2) by X_i and taking the conditional expectation $E(\cdot|Z_i)$ yields the following:

$$E\left(X_iY_i\middle|Z_i\right) = E\left(X_iX_i'\middle|Z_i\right)\delta(Z_i) \tag{3}$$

because $E(X_iu_i|Z_i) = 0$. Rearranging (3) we get

$$\delta(Z_i) = \left[E\left(X_iX_i'\middle|Z_i\right)\right]^{-1}E\left(X_iY_i\middle|Z_i\right) \tag{4}$$

The parameter function $\delta(Z_i)$ then can be estimated by

$$\hat{\delta}(Z_i) = \left[\sum_{i=1}^{n} X_iX_i'K(Z_i, z)\right]^{-1}\sum_{i=1}^{n} X_iY_iK(Z_i, z) \tag{5}$$

where $K(Z_i, z)$ is the kernel function. There are several ways to specify the kernel function (for example, Gaussian, uniform, Epanechnikov, etc.), and several ways to specify the bandwidth (for instance, least-squares cross-validation or likelihood cross-validation).[6] In our study, we chose Gaussian kernel functions and least-squares cross-validation to select bandwidths.

2.2.1. Constrained estimation

Although the SPSC model is very flexible, the price one has to pay is a higher probability of empirical violations of economic conditions. According to neoclassical production theory, marginal products should be non-negative. However, empirically there are cases when marginal products (elasticities) are negative. Since this is counter-intuitive, it is desirable to impose constraints to make them non-negative. One way to mitigate this potential problem is to consider constrained estimation. There is an extensive literature on constrained semiparametric estimation (see Henderson & Parmeter, 2015, ch. 12, for an overview). In this study, we followed the constraining approach described by Bhaumik, Dimova, Kumbhakar, & Sun (2018). To impose the constraints, we rewrite (5) as

$$\hat{\delta}(Z_i) = \sum_{i=1}^{n} A(X_i, Z_i, z)Y_i \tag{6}$$

where $A(X_i, Z_i, z) = \left[\sum_{i=1}^{n} X_iX_i'K(Z_i, z)\right]^{-1}\sum_{i=1}^{n} X_iK(Z_i, z)$. This equation can be written as

$$\hat{\delta}(Z_i) = n \cdot \sum_{i=1}^{n} A(X_i, Z_i, z) \cdot p_u \cdot Y_i \tag{7}$$

where $p_u = n^{-1}$ denotes uniform weights. In this formulation we introduce a re-weighting (from the uniform weight) scheme that changes the dependent variable as little as possible, but at the

[4] The relationship can be interpreted as causal under the *ceteris paribus* assumption. That is, if risk-related variables change holding everything else constant, the relationship can be interpreted as causal (Wooldridge, 2015).

[5] See Li, Huang, Li, & Fu (2002) and Li & Racine (2010), for example.

[6] For details on these issues see, for example, Henderson & Parmeter (2015).

same time avoids negative input elasticities. We can specify the constrained semiparametric smooth-coefficient estimator as

$$\hat{\delta}^*(Z_i) = n \cdot \sum_{i=1}^{n} A(X_i, Z_i, z) \cdot p_i \cdot Y_i \tag{8}$$

where p_i denotes the observation-specific weights, and $\sum_i p_i = 1$. To select optimal p_i we minimize $\sum_i (p_i - p_u)^2$ subject to $\beta(Z_i) \geq 0$, by using quadratic programming (the quadprog package in R).

2.2.2. Marginal effects of the Z variables

The change in the expected value of Y_i (which is in logs) with respect to a change in a particular element of X_i, say $X_{ji} = X_j (j = 1, 2, \ldots)$ (which is also in logs), is $\beta_j(Z_i)$, based on Eq. (1). That is, the input elasticities $\beta_j(Z_i)$, are defined as

$$\frac{\partial \hat{Y}}{\partial X_j} = \beta_j(Z_i). \tag{9}$$

Since these input elasticities are functions of Z_i, we can get observation-specific values for them so long as the Z variables are observation-specific. We can also report mean and/or quantiles or provide density plots of them.

The calculation of the change in the expected value of Y_i with respect to a change in a particular element of Z_i, say Z_{ki} $(k = 1, 2, \ldots)$, is somewhat less trivial. Based on Eq. (1), it is defined as:

$$\frac{\partial \hat{Y}}{\partial Z_{ki}} = \frac{\partial \alpha(Z_i)}{\partial Z_{ki}} + \sum_{j=i}^{J} X_j \frac{\partial \beta_j(Z_i)}{\partial Z_{ki}} \tag{10}$$

The marginal impacts of the risk-related Z variables then depend on each of the Z and X variables included in the analysis. The first component of (10) is the direct marginal impact of Z_{ki}, and the second component is the indirect marginal impact of Z_{ki}, which can be further decomposed into J elements of X.

3. Data

We use a primary survey of smallholder households, conducted during 2015 in the states of Punjab, Haryana, and Uttarakhand in India. Rice is one of the three most important food crops in the world, forming the staple diet for 2.7 billion people. Around the world, rice is grown on 150 million hectares of land, producing 573 million tons of rice, with average productivity of 3.83 tons/ha. In India rice accounts for 40% of food grain production. As a staple, rice represents a primary source of calories for many smallholder families in India. It plays a vital role in food security, and its cultivation is a primary source of income for these families (Naresh, Mishra, & Singh, 2013). India is the largest producer of basmati rice, accounting for about 70% of world production. The Green Revolution that brought food security and increased incomes for farmers has shown signs of fatigue and empirical evidence suggests that natural resources may be reducing productivity. Additionally, concern for deteriorating environmental health, the growing demand from consumers and importers for safe and high-quality products, and opportunities for premium returns have motivated farmers to look to sustainable agriculture, also known as organic farming.[7]

The International Food Policy Research Institute (IFPRI) South Asia office designed the questionnaire and collected the information from smallholders who specialized in organic basmati rice (OBR[8]) production. Farmers in the survey were chosen randomly from a list of farmers engaged in organic basmati rice production. A total of 923 OBR farmers were included in our analyzed sample. Of these, 395 were located in Punjab (198 from Amritsar district, 197 from Patiala district), 333 were in Haryana (170 from Karnal district, 163 from Kaithal district), and 195 were from Uttarakhand (from Dehradun district). The survey, 19 pages long, consisted of several modules. The first module queries related to general information about household head and other socio-economic characteristics, land (owned and leased), farming enterprises and food safety issues. The survey collected information on costs and return of basmati rice, including variable and fixed costs. A separate module in the same survey collected information on assets (farm and non-farm), income (farm and non-farm sources) and expenditure (food and non-food expenditures). The next module in the survey collected information on social networks and on risk - specifically information on the risk faced, risk preferences and responses to lottery choices (gambles). The next module collected information on access to infrastructure (roads, banks, distance to cities, post office and towns). The final module collected information on good agricultural practices.

3.1. Variables used in the production function

Drawing on the survey data, we specified the production function with gross revenue as output (Y), and three inputs: land (X_1), measured in acres; labor (X_2), measured in man-year equivalents; and materials (X_3), measured in Rupees.

3.2. Risk-related variables included in the model

We drew on subjective expected utility theory (SEU) (Savage, 1954) for the choice of risk-related variables for inclusion in the productivity analysis. Although SEU is a normative theory of risky decision, and therefore is not intended to describe what farmers do, it can be used as a guide for what variables to include when accounting for risk. Under risk, the farmers will not know for sure the relationships between their choices of inputs and the output in a production relationship (production function). Hence there is a risk, which we expect will influence the farmers' behavior and input choices. SEU is built on the assumption that risky choices can be separated into two components: i) the farmers' subjective beliefs about the uncertainty affecting the outcome of alternative actions, and hence their perceptions of the riskiness; ii) the preferences of the farmer for the various consequences that might arise from the choice (Hardaker, Lien, Anderson, & Huirne, 2015). Beliefs in the form of perceptions of uncertainty are typically quantified as subjective probabilities. Preferences for risky outcomes are typically quantified via a utility function, in which the curvature of this function reflects the farmer's degree of risk aversion. In this study, we assumed beliefs about uncertainty could be aggregated into observable variables of farmers' perceptions of risk, while variables for the degree of risk aversion account for preferences about uncertain outcomes. We also assume that input decisions are made prior to knowing what the output will be. Thus, inputs can be treated as predetermined and therefore uncorrelated with the noise term. We

[7] In a recent study, Mishra, Kumar, Joshi, D'Souza, & Tripathi (2018) noted that organic production is highly susceptible to weather and pest risks. In particular, organic basmati rice (OBR[8]) growers face higher production risks, compared to conventional producers, because of the absence of commercial fertilizer and pesticides for organic production. Many studies have found that Indian rice farmers are risk-averse (e.g., Binswanger, 1980; Ballivian & Sickles, 1994). There have been a number of studies of the risks of organic rice farming in India. For example, Mishra et al. (2018) assessed the impact of production risks on the probability of smallholders adopting contract farming (CF) in OBR farming and analyzed the impact of CF adoption on productivity, prices received, and the livelihood of OBR producers.

[8] Basmati rice is long and slender-grained aromatic variety of rice, well-suited for organic production owing to its lower nutritional requirement Surekha et al. (2010). Further, OBR is one of the major agricultural export commodities that bring in much-needed foreign exchange. Because of its high production and export volumes, OBR has received much attention from both growers and policymakers.

Table 1
Eliciting risk preferences gamble.

Choice (50/50 gamble)	Low payoff	High payoff	Expected return	Standard deviation	Implied CRRA range
Gamble 1	30	30	30.0	0.0	$r > 3.0$
Gamble 2	25	40	32.5	7.5	$1.0 < r < 3.0$
Gamble 3	20	50	35.0	15.0	$0.6 < r < 1.0$
Gamble 4	15	60	37.5	22.5	$0.4 < r < 0.6$
Gamble 5	10	70	40.0	30.0	$0.0 < r < 0.4$
Gamble 6	0	80	40.0	40.0	$r < 0.0$

Notes: (*i*) The risk aversion is reported as ranges in coefficients of relative risk aversion (*CRRA*). The *CRRA* function is $U = \frac{(payoff^{(1-r)})}{(1-r)}$. The CRRA limits is the value or r that gives the same utility for Gamble X as for Gamble $X+1$. (ii) Source: Authors' calculation.

were able to draw on the survey data, described above, using farmers' answers to lottery questions, converted into measures of risk aversion, and use their answers to questions about risk to reflect their beliefs about the uncertainty they face.

In practice, integrating beliefs and preferences to make wise choices in a risky world is a challenging task. More experienced farmers may be able to draw on experience to make better choices in risky production than those less experienced. Experience may also help farmers cope better with adverse events that occur. In summary, the risk-related variables, assumed to influence farmers' behavior, that we included in the model are as follows:

1. Differences in attitude to risk. Risk aversion means that farmers may be willing to reduce some expected profits for a reduction in risk. They may cut back or increase some inputs that then will influence the output. They also may seek to cope with risk by avoiding more risky forms of production. These kinds of actions are likely to affect their productivity.
2. Differences in perceptions of risk. Farmers are assumed to form opinions about the likelihood of occurrence of different outcomes of uncertain factors (weather, prices, output quantity and quality, pest and disease outbreaks, etc.). The opinions they form are likely to affect management decisions such as choices of levels of input use, which then influence their productivity.
3. Differences in management skills. Farmers with more experience may be able make better strategic choices, or may cope better with adverse outcomes, when they occur, than farmers with less experience.
4. Differences in uncontrolled variables. Available data and model limitations can never exactly match reality. There will always be something that is not explained by the data and the model used. There is always heterogeneity among the farms/farmers that cannot be controlled for in a parametric model. With a flexible model (non-parametric or semiparametric model), (some of) this heterogeneity can be accounted for.

3.3. Measuring degrees of risk aversion

In the literature, several techniques have been used to elicit decision-makers' or farmers' risk attitudes (Charness, Gneezy, & Imas, 2013). We constructed the variable for attitude to risk (Z_1) based on the hypothetical risk preference elicitation approach included in our survey. It is a gamble-choice elicitation method, based on that of Eckel & Grossman (2008). In the survey, the farmers had to select one most-preferred gamble from among six (see Table 1). Fig. 1 shows the distribution of results. For each farmer's response, we calculated a coefficient of relative risk aversion (*CRRA*). As shown in Fig. 1, for ($r > 3.0$) we used $CRRA = 3.5$, for the range ($1.0 < r < 3.0$) we used $CRRA = 2.0$, for the range ($0.6 < r < 1.0$) we used $CRRA = 0.8$, for the range ($0.4 < r < 0.6$) we used $CRRA = 0.5$, and for the ranges ($0.0 < r < 0.4$) and ($r < 0.0$) we collapsed these into one range ($r < 0.4$) and defined it as

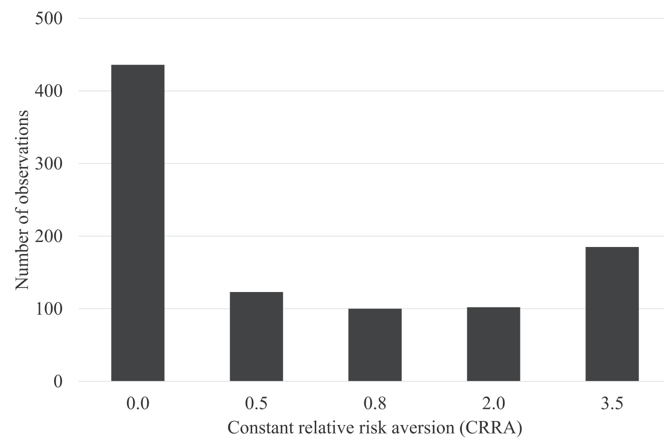

Fig. 1. Distribution of the respondents/farmers on reported risk attitude.

Table 2
Descriptive statistics (N = 923).

Variables	Label	Mean	Std. dev.	Min	Max
Output					
Gross revenue (Rupees)	Y_1	149,520	167,001	4650	986,000
Inputs					
Land (acre)	X_1	9.28	11.65	0.25	146.00
Labor (man-year equivalents)	X_2	0.32	0.33	0.02	2.15
Materials (Rupees)	X_3	34,632	38,838	1475	421,660
Risk-related Z variables					
Attitude toward risk, CRRA	Z_1	1.05	1.35	0.00	3.50
Perceptions of risk (1–5)	Z_2	3.22	0.70	1.00	5.00
Risk management skills (experience)	Z_3	27.99	13.28	1.00	65.00

Note: Source: IFPRI-India survey.

$CRRA = 0.0$, i.e., risk-neutral. Somewhat unexpectedly, about 46% of the farmers chose the risk-neutral gamble.[9]

3.4. Perceptions of risk and risk management skills

The variable for perceptions of risk (Z_2) was constructed as a summated scale variable, based on three variables from the survey. The three variables were *'farmers' perceptions of the risk of producing basmati rice of low physical quality that does not meet buyer requirements'* (we call this the product quality risk), *'farmer's perceptions of the risk of losing basmati rice production due to weather'* (weather risk), and *'farmers' perceptions of the risk of losing basmati rice production due to pest and insects'* (pest risk). The survey queried OBR smallholders on the above three risk questions, each on a 5-point Likert scale.

Accounting for risk management skills is a complex issue, since many variables can influence skills. However, since we expect experience to be important in skill development, we used farmers' experience in farming (in years) (Z_3) as a proxy for risk management skills.

Table 2 presents the descriptive statistics of the variables used in the analysis. The average farm size was about 9.3 acres but, as Table 2 reveals, there was significant variability in farm size. The average OBR smallholder had about 28 years of farming experience. Table 2 shows that gross revenue from OBR farming averages INR[10] 149,520; however, the table also reveals significant variability in gross revenue. Additionally, materials show significant variability among OBR farmers. Materials for OBR smallholders aver-

[9] Our results are somewhat in contrast to the earlier study by Binswanger (1980), who found that farmers in India were moderately risk-averse.

[10] The exchange rate was 1 USD = 65 INR (Indian rupees) at the time of the survey.

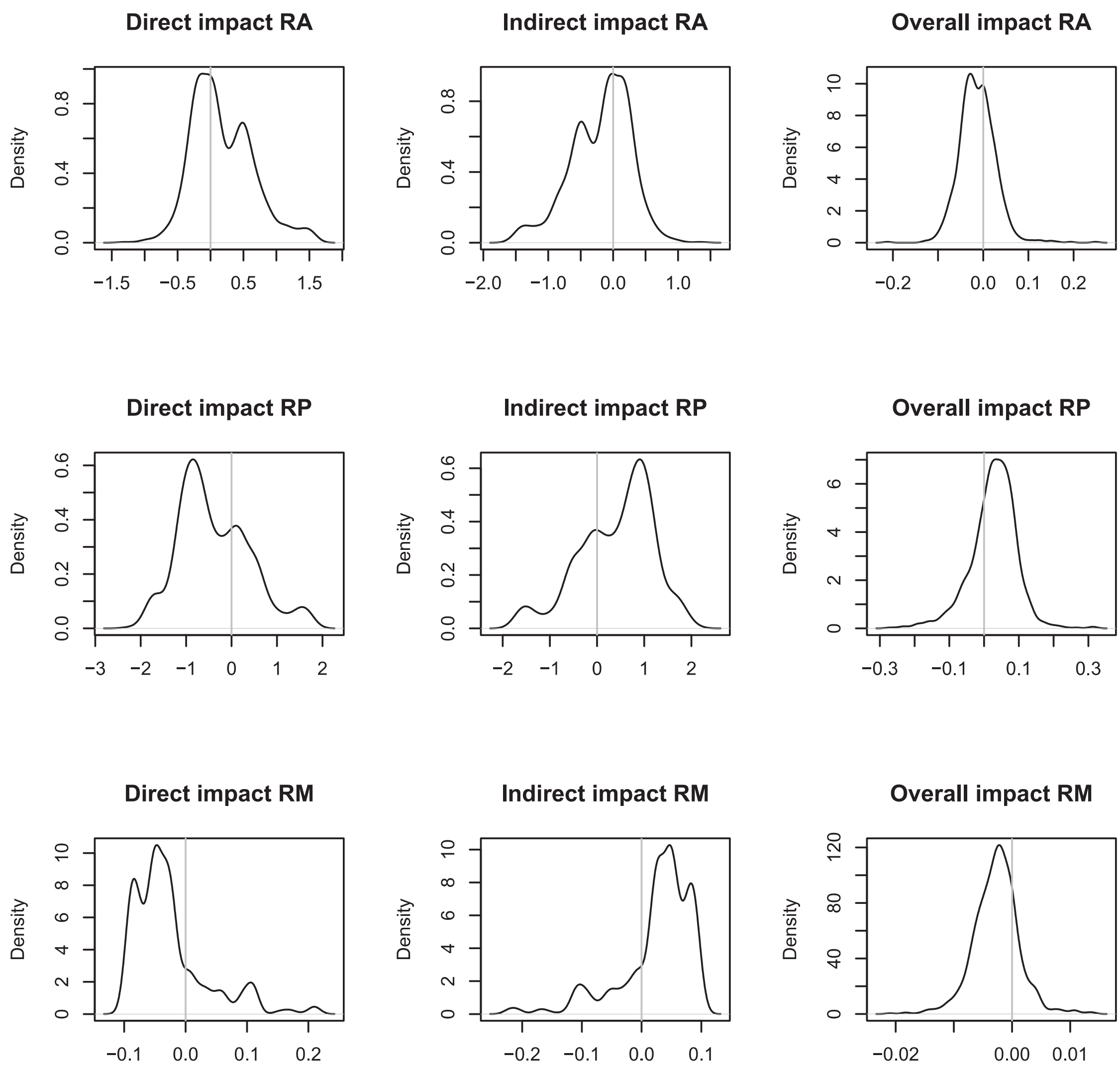

Fig. 2. Density plot of direct, indirect and overall marginal impacts (OME) of attitude toward risk ($Z_1 = RA$), perceptions of risk ($Z_2 = RP$), and risk management skills ($Z_3 = RM$).

ages INR 34,632. Finally, estimates of attitude toward risk (CRRA) reveal that OBR smallholders are slightly risk-averse, on average, with a CRRA of 1.05.

4. Empirical results

With the unconstrained semiparametric smooth-coefficient estimator, about 10% of the sample had negative input elasticities for land.[11] This is a counter-intuitive result, not in line with economic theory. Hence, we present below the results based on the constrained[12] SPSC estimator.[13] We first, in this section, present our findings regarding how productivity depends on the attitudes to risk of the farmers, their subjective beliefs about the risks they face, and their previous experience, before we present our findings regarding elasticities and returns to scale.[14]

4.1. Direct, indirect, and overall marginal impacts of the Z variables

Fig. 2 reports the direct, indirect, and overall marginal impacts of the risk-related variables on productivity (gross revenue). The results are mixed. The risk-related variable of attitude toward risk (Z_1), measured with our CRRA variable, had a positive direct impact on productivity for some, but for others, the impact is negative. The same holds for the indirect impact. The overall mean impact of Z_1 on productivity was somewhat negative. In other words, the estimates indicate that an increase in the degree of risk aversion reduces farmers' productivity, on average, consistent with the findings by Ballivian & Sickles (1994) in their study of multi-output cropping of Indian farmers. Our findings is also consistent with Lien et al. (2017). This result seems, at first glance, counter-intuitive, since risk-averse farmers typically will be willing to sacrifice some expected profit for a reduction in risk, often by reducing inputs that increase unpredictability/variance of output and/or by

[11] This finding suggests that risk-averse farmers are allocating land to different crops and/or labor to non-agricultural activities (Van Campenhout & Bizimungu, 2018).

[12] The unconstrained results are available from the authors upon request.

[13] We also tested whether the semiparametric model is necessary using the test procedure described in Bhaumik et al. (2018), or whether OLS is sufficient to estimate the augmented production function. We found that the specification test rejected the OLS specification in favor of the semiparametric approach, at the 1% level of significance.

[14] In Table A.1 in Appendix the main result estimates are given.

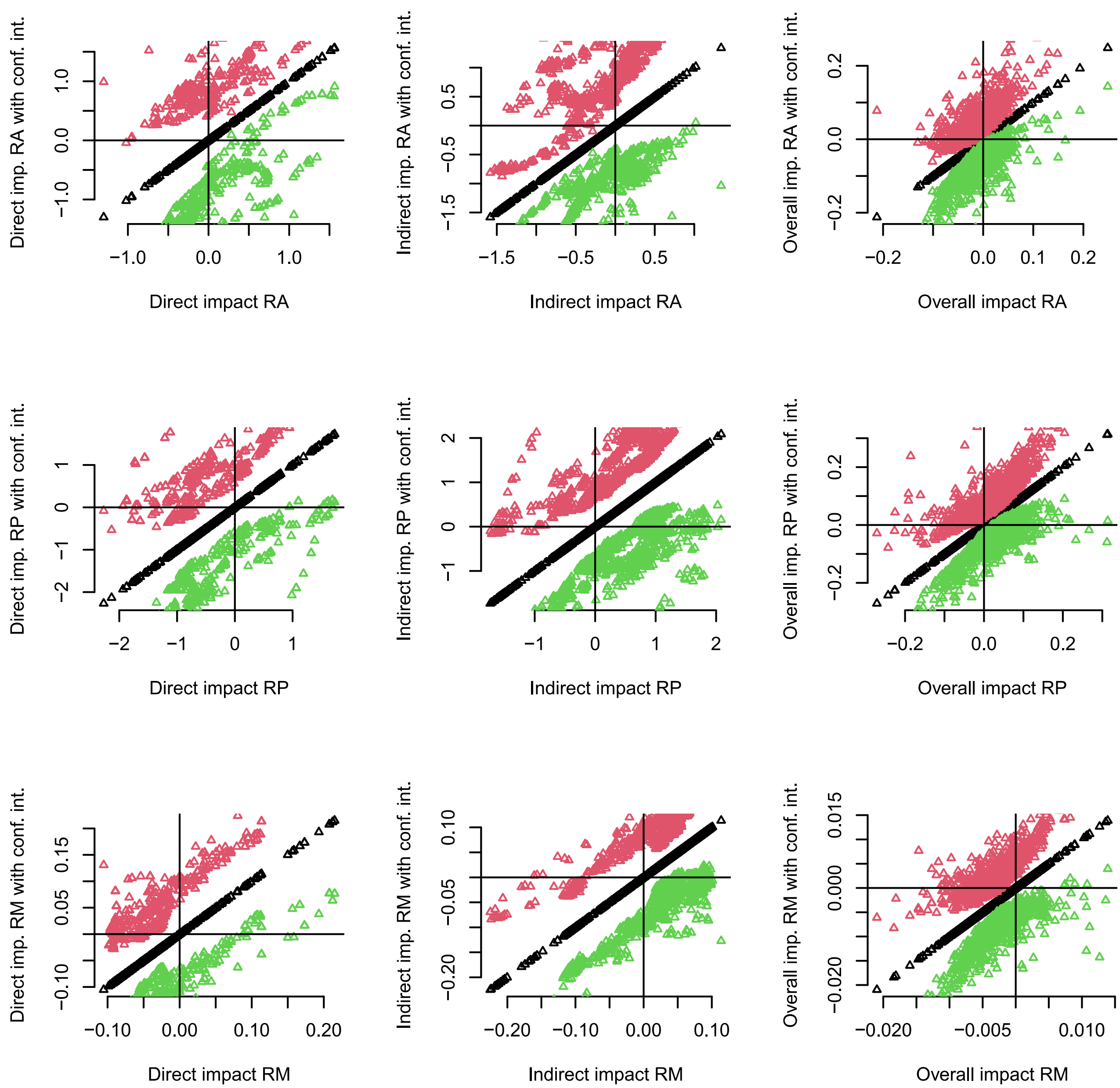

Fig. 3. 45° plot of estimated gradients for attitude toward risk ($Z_1 = RA$), perceptions of risk ($Z_2 = RP$), and risk management skills ($Z_3 = RM$). Note: The single-point estimates against the same single-point estimates along the 45-degree line are represented with black triangles △. The upper confidence bounds are found by adding and subtracting, respectively, twice the standard error from the single-point estimate are represented by red triangles △ and green triangles △. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

avoiding risky forms of production. Such actions may (or may not) result in an increase in measured productivity. We also know that innovators, who are presumed to be leaders in improving productivity, are typically less risk-averse (e.g., Naldi, Nordqvist, Sjöberg, & Wiklund, 2007). In other words, how attitudes to risk affect productivity is an empirical question that we sought to clarify in this study.

The variable perceptions of risk (Z_2) had somewhat the opposite impact to that of Z_1. On average, perceptions of risk had a negative direct impact but had positive indirect and overall impacts on productivity. One possible explanation of this findings for perceptions of risk could be that farmers who rate such risks as quality risks, weather risks and pest risks more highly than others will typically be less willing to invest in highly intensive but risky production and technology. Farmers who are more aware of the likelihood of bad occurrences because of uncertain factors then seems to adapt sufficiently well to increase their productivity. This result is also consistent with the findings for onion growers in India (Khanal, Mishra, & Lien, 2021) and also for Norwegian dairy farmers (Lien et al., 2017). Finally, the risk-related variable of risk management skills (Z_3) had, on average, and somewhat counterintuitive, a negative impact on productivity. While it might be expected that increased experience enables farmers to better manage complex risky choices, that may not be so. Increased experience also typically means increased age of the farmer, which could affect risk management adversely, for example, via more conservative risk management choices.

To explore the above-discussed marginal impacts of the Z variables further, we used the method described by Henderson, Kumbhakar, & Parmeter (2012) to visualize results. Because the SPSC model gives observation-specific estimates (e.g., for marginal impacts or other measures), we generate observation-specific

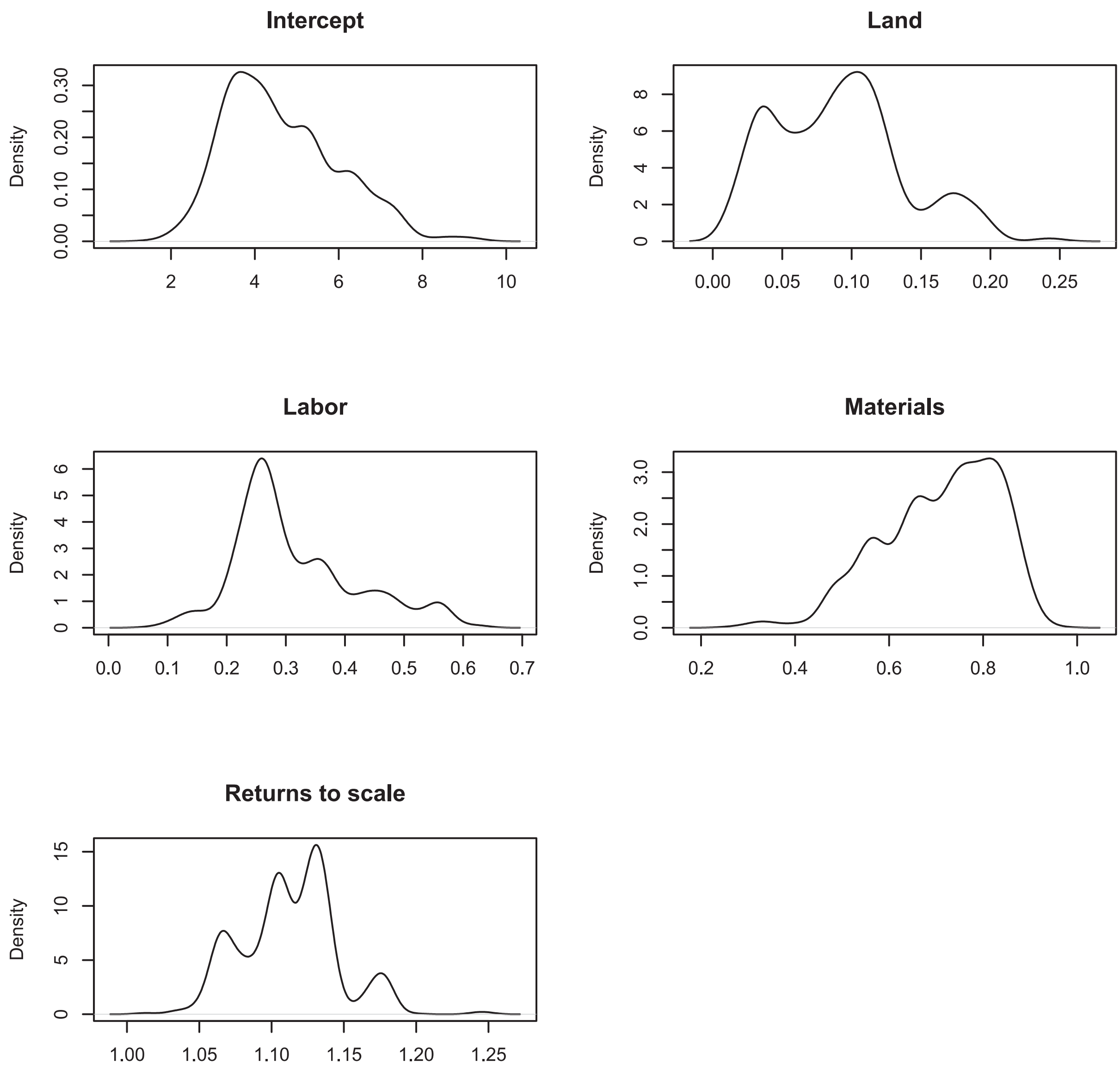

Fig. 4. Kernel density plot of the intercept, the elasticities and the returns to scale.

confidence intervals for the estimates by using the residual-based wild bootstrap method (Li & Racine, 2010). We first plotted the single-point estimates against the same single-point estimates (represented with black triangles (△)) along the 45-degree line. Thereafter, we generated upper (red triangles, △) and lower (green triangles, △) confidence bounds by adding and subtracting, respectively, twice the standard error from the single-point estimates. This gave us an observation-specific confidence interval for each point estimate. Finally, we added a horizontal line at zero and a vertical line at zero to the graph. When the upper and lower confidence bounds are both in the upper right (lower left) quadrant, then the single-point estimate for that observation is positive (negative) and statistically significant from zero. When the upper and lower confidence bounds straddle the horizontal line, the single-point estimate is not statistically different from zero.

As reported in Fig. 3, the impacts of risk-related variables on productivity were mixed and not always statistically significant from zero. Variability in the estimates shows a heterogeneous impact of the risk-related variables. That is, not all the farmers reacted to risky situations in the same fashion. However, a large proportion of the observation-specific parameter estimates were placed in the confidence interval in the upper left and lower right quadrants, meaning that these are statistically (either positive or negative) insignificant.

4.2. The estimated elasticities and returns to scale

The SPSC model does not give 'standard' parameter estimates since the 'parameters' are non-parametric functions. As a result, no exact comparison with the standard approach of presenting parametric estimates in a table with standard errors can be made (Henderson & Parmeter, 2015). The 'parameters' are observation-specific, or more precisely, they are the gradient estimates which in the CD case represent the elasticities of output with respect to the inputs. In Fig. 4, we plot the kernel density of the intercept, the input elasticities, and the returns to scale (sum of the input elasticities). Fig. 4 shows that the elasticity with respect to materials is the highest (ranges from 0.26 to 0.96), followed by labor (ranges from 0.06 to 0.63) and land (ranges from 0.01 to 0.25). Returns to scale range from 1.01 to 1.25, implying increasing returns to scale.

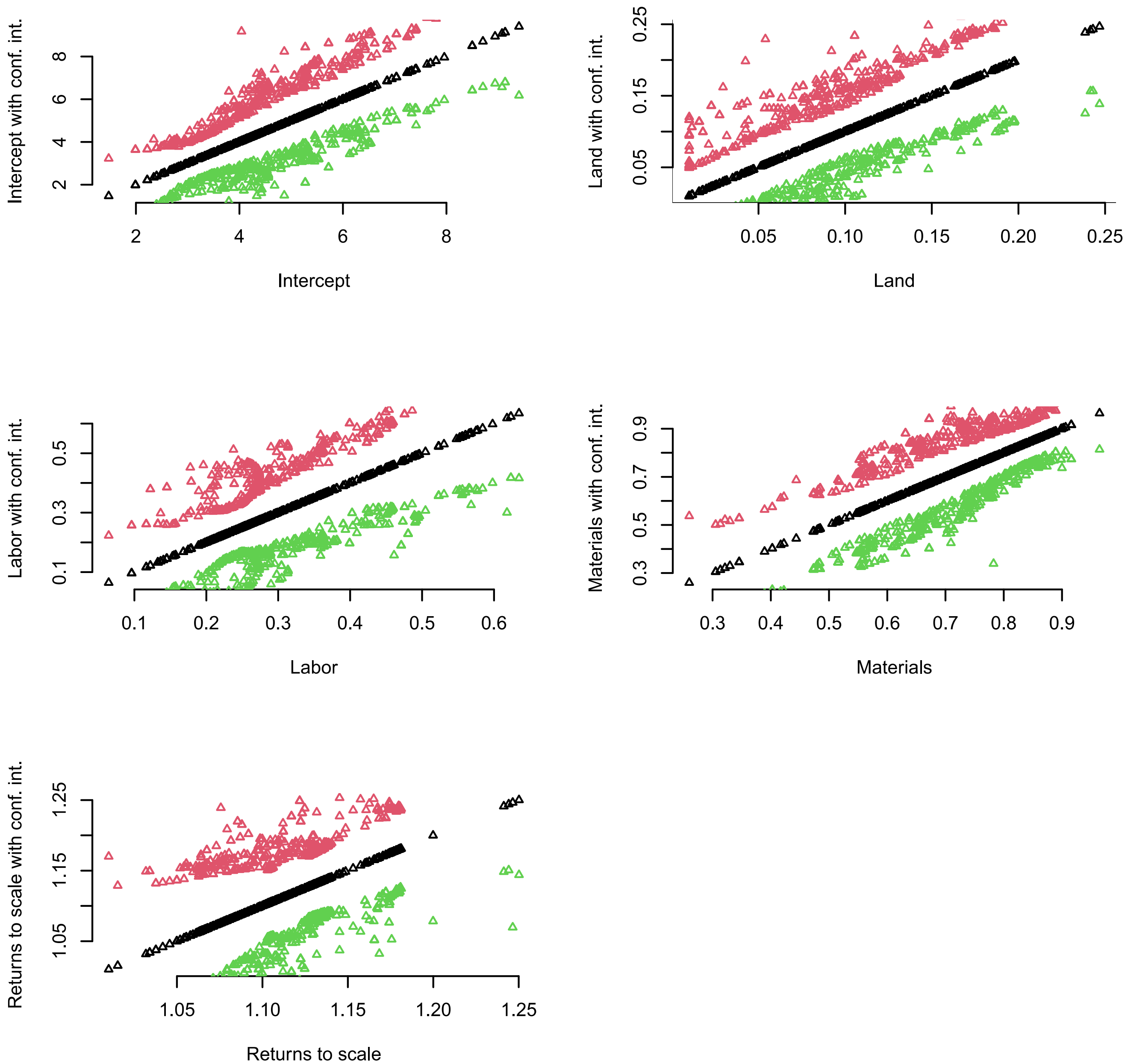

Fig. 5. 45° plot of estimated gradients for the intercept, three coefficients (land, labor, materials) and returns to scale (RTS).

This result suggests that OBR producers in India could reduce their costs of production by increasing the scale of their farming operations.

Fig. 5 shows both the distribution of the single-point estimates for the intercept; the elasticities for land, labor, and materials; and returns to scale (the black triangles (△) and their statistical significance. For the three inputs (land, labor, and materials), the elasticities for the whole sample are positive and statistically significant from zero. Fig. 5 also shows statistically significant increasing returns to scale for the entire sample. Some OBR farms have returns to scale close to 1.0, and some OBR farms have returns to scale at about 1.25.

As a simple test of whether risk-related variables result in scale inefficiency, we calculated the correlation between risk-related variables and farm size, where farm size measured with gross revenue. We found that attitude toward risk, measured with our CRRA variable, had statistically significant negative correlation (-0.18) with farm size, consistent with what Ballivian & Sickles (1994) also found. Perceptions of risk had a statistically significant positive correlation (0.16) with farm size, while experience had an statistically insignificant correlation (0.05) with farm size.

5. Concluding remarks and implications

Accounting for risk in productivity analysis is a complex task. In this study we analyze the effects of farmers' risk on productivity where the production function is generalized to be specific to risk variables. This resulted in a semiparametric smooth-coefficient (SPSC) production function. A novelty of the SPSC approach is that it is very flexible and gives observation-specific intercept and slope parameters that are conditional on some risk-related, Z variables. This allows for in-depth analyses of marginal effects, returns to scale, etc. Our focus differs from earlier risk/productivity studies by not directly focusing on the impact of risk on production but how productivity depends on the attitudes to risk of the farmers, their subjective beliefs about the risks they face, and their previous experience.

Of the risk-related variable attitude towards risk, we found that OBR farmers with high degrees of risk aversion had lower productivity than less risk-averse or risk-neutral farmers. Regarding perceptions of risk, farmers who are highly concerned about production, weather and pest risks, compared their counterparts, had higher productivity. Our analysis also showed that these farmers have increasing returns to scale, implying that they can reduce their costs of production by increasing farm size.

What can policymakers do regarding the negative impact farmers' risk aversion has on productivity? Obviously, they cannot change farmers' risk attitudes. However, measures that can reduce the riskiness of farming will mitigate the impacts or risk aversion. Disseminating more information about best-integrated pest management (IPM) practices, improving irrigation systems, encouraging the use of more resilient crop varieties and other sound agronomic recommendations would make yields more certain, and in that way reduce the impact of farmers' risk aversion in farming practice. It would be wise for farm advisers to consider whether risk-averse farmers would benefit from diversifying their cropping or their sources of income, by some family members engaging in some forms of paid employment. Another option for risk reduction is more use of contract farming, in the form of forward-selling the crop at an agreed price (Mishra et al., 2018). Crop yield insurance also could be considered, and the Government itself should strive for not be a risk-source by ill-considered changes in regulations and laws affecting agriculture (Hardaker, Fleming, & Lien, 2009).

The positive impact on productivity of farmers concerned about production might suggest that alerting more farmers to the kinds and sources of risks in rice farming might encourage changes in crop management that would improve productivity. On the other hand, since our findings imply that reducing the subjective uncertainty leads to higher productivity, a policy of supplying more information might be good. Some relevant options might be long-range weather forecasts and market outlook information (if reasonably reliable), more information about contract farming, and more education and training, to mention a few examples.

Our results demonstrate that this semiparametric smooth-coefficient regression approach allows for an in-depth analysis of factors affecting productivity at the farm level. In principle, the method provides for farm-specific measures for almost everything, and the method opens opportunities for useful benchmarking analysis.

Appendix A. More results

Table A.1
Results based on the constrained SPSC estimator.

Variables	Q_{10}	Q_{25}	Q_{50}	Q_{75}	Q_{90}
Inputs					
Intercept	3.1965	3.5766	4.3741	5.44570	6.5363
Land	0.0158	0.0522	0.0908	0.11458	0.1646
Labor	0.2174	0.2507	0.2824	0.37013	0.4755
Materials	0.5521	0.6376	0.7322	0.80988	0.8523
RTS	1.0647	1.0913	1.1122	1.13333	1.1449
Direct impact of risk-related variables					
Attitude toward risk	-0.3207	-0.1848	0.0887	0.49502	0.7502
Perceptions of risk	-1.1625	-0.9531	-0.5919	0.16278	0.5974
Risk management skills (experience)	-0.0867	-0.0676	-0.0410	-0.01404	0.0623
Indirect impact of risk-related variables					
Attitude toward risk	-0.7930	-0.4993	-0.1031	0.15988	0.3086
Perceptions of risk	-0.5726	-0.1219	0.6037	0.98790	1.2268
Risk management skills (experience)	-0.0635	0.0104	0.0380	0.06426	0.0845
Overall impact of risk-related variables					
Attitude toward risk	-0.0577	-0.0381	-0.0151	0.01003	0.0323
Perceptions of risk	-0.0571	-0.0073	0.0325	0.06882	0.0952
Risk management skills (experience)	-0.0071	-0.0050	-0.0025	-0.00037	0.0016

(*continued on next column*)

Table A.1 (*continued*)

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