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Comparing the use of risk-influencing production inputs and experimentally measured risk attitude
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Do decisions of Indonesian small-scale rubber farmers match?

Stefan Moser and Oliver Mußhoff

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Keywords: Holt-Laury lottery, Just-Pope production function, output risk, rubber, Indonesia

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Comparing the use of risk-influencing production inputs and experimentally measured risk attitude: Do decisions of Indonesian small-scale rubber farmers match?

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Abstract

This article compares the use of risk-increasing and risk-reducing production inputs with the experimentally measured risk attitudes of farmers. For this purpose, the Just-Pope production function indicates production inputs' influence on output risk and a Holt-Laury lottery is used to measure the producers' risk attitude. We test whether more risk averse farmers use more risk-reducing and less risk-increasing production inputs. Therefore, we apply a unique data set which includes 185 small-scale farmers which are producing rubber on 260 plots on the island of Sumatra, Indonesia. The Just-Pope production function indicates that fertiliser usage has a risk-reducing effect, whereas herbicide usage and plot size have risk-increasing effects. For labour and plantation age, the influence on output risk is ambiguous. By including the outcome of a Holt-Laury lottery into the analysis, we found the expected result that more risk averse farmers use more (risk-reducing) fertiliser and less (risk-increasing) herbicides. These consistent results provide an example for the external validity of measuring risk attitude with the Holt-Laury lottery.

JEL classification: C91, C93, Q12

Keywords: Holt-Laury lottery, Just-Pope production function, output risk, rubber, Indonesia

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1. Introduction

Yield fluctuations caused by extreme weather conditions, diseases or the adoption of new technologies have the potential to lead to dramatic changes in income, thus making farming a risky business (Key and MacDonald, 2006). The combination of output risk and the risk attitudes of farmers are among the main drivers for production decisions in agriculture (Chavas et al., 2010). Moreover, Hellerstein et al. (2013) discuss the importance of understanding the risk attitude/production decision relationship since it helps to design policies which can accommodate changing economic and environmental circumstances as well as it supports farmers to make appropriate reactions. However, the precise manner in which risk and risk attitude affect farmer's production decisions is not easy to determine (Just, 2001; Just and Pope, 2003).

Analysing risk attitude is a primary focus in the research field pertaining to risk in agriculture (Chavas et al., 2010). A long proven method for measuring risk attitude is through experiments (Binswanger, 1980). In this context, Holt and Laury (2002) developed a well-accepted method to measure the risk attitude (Anderson and Mellor, 2008). Ihli and Musshoff (2013) further adapted this Holt-Laury (HL) risk measure to be applied to people with limited level of school education. By taking this adaptation into consideration, we can apply this method for measuring risk attitudes in rural areas of developing countries.

To evaluate the production decisions of farmers, we focus on output risk, i.e., output variance. Therefore, we use a well-accepted and often applied method developed by Just and Pope (1978; 1979) for investigating output risk in agriculture. This method shows production inputs' simultaneous influence on the output level and output risk in agricultural production systems. Several studies have applied and extended this approach for different contexts and purposes, thus proving its relevance (Barrett et al., 2004; Di Falco and Chavas, 2009; Gardebroek et al., 2010; Tiedemann and Latacz-Lohmann, 2013; Chavas and Holt, 1996; Bar-Shira et al., 1997; Isik and Khanna 2003; Kumbhakar, 2001; 2002a; 2002b; Abdulkadri, 2003; Kumbhakar and Tveterås, 2003).

In the literature, a discussion regarding the external validity (sometimes termed generalisability) of experimentally obtained field behaviour results is in progress. We denote external validity of experimental results as "insights gained in the lab can be extrapolated to the world beyond" (Levitt and List, 2007: 153), thus, field behavior is defined as behavior that occurs outside of experiments. However, Levitt and List (2007) are sceptical about the external validity of experimentally obtained results. They argue that the lab differs systematically from most naturally occurring environments which yields to results that are not always generalisable. Conversely, Camerer (2011) argues that experimental results are externally valid if sufficient information is available. He states that "if many experimental and field data sets were combined, with sufficient variation among variables […], a 'Lab' dummy variable would not be significant" (Camerer, 2011, p.6). According to Roe and Just (2009), in economics there is typically a trade-off between the external and internal validity of results, with field data on the one end and lab data on the other end of the spectrum. They suggest alleviating this tension by applying field or natural experiments. However, various approaches to the problem of external validity of experimental results can be seen in the literature. Certainly, more examples which directly compare experimental results and field behaviour would be appealing.

Farmers' production decisions are a good option for measuring their behaviour towards risk in the field because these decisions have a crucial influence on farmers' income and, thus, reflect a major risk in the lives of farmers. By comparing this field behaviour towards risk with an experimentally measured risk attitude, we can determine if results found in the experiment have external validity to the behaviour in the field. In other words, we test if the revealed risk attitude is consistent with the experimentally measured risk attitude.

Investigations comparing field decisions towards risk and experimentally measured risk attitudes have already been completed. Hellerstein et al. (2013) predict farming decisions related to diversified operations or to having crop insurance with a lottery-choice mechanism that measures farmers' risk attitude and found contradicting results between field and experimental decisions. Further examples were given where lottery choices are used to predict agricultural decisions which include risk, e.g., crop diversification in Peru, where experimental results helped with predicting field behaviour (Engle-Warnick et al., 2007); decisions towards coffee production in Uganda, where the stated preference explained production decisions (Hill, 2009); or adoption habits with regards to genetically modified crops in the USA, where results show a small effect through risk aversion (Barham et al., 2012). With respect to non-agricultural decisions, Anderson and Mellor (2009) found consistent relationships between experimentally measured risk attitudes and decisions regarding health and safety. It seems that currently there is no definite answer to whether experimentally measured risk aversion is reflected in the field behaviour, which requires further investigations. Furthermore, experimentally measured risk attitude and production decisions towards risk, evaluated with a Just-Pope (JP) production function, have not been compared thus far. This is especially relevant, since influencing output risk with the input choice is a tool which practically every farmer has the ability to utilize. Thus, farmers can manage income risk, independent of the availability of other tools like insurance, production diversification or non-farm labour.

On the islands of Sumatra and West Kalimantan, 72% of the Indonesian rubber output is produced (Arifin 2005). Rubber is a major crop trees and together with oil palm it generate the majority of farmers' income in the Jambi province on Sumatra. In this province, 52% of the workforce is employed in the agricultural sector and about the half of the cultivated land is used for rubber production, which usually is managed by small-scale farmers (Statistical Year Book of Estate Crops, 2012). This shows the economic relevance of rubber for the region, and therefore, income risk caused through output risk in rubber production is a crucial concern in this region.

The objective of this paper is to determine whether farmers' production decisions towards risk are consistent with the risk attitude measured in an experiment. We test this for the case of small-scale rubber farmers in Jambi province on Sumatra, Indonesia. To determine farmers' field behaviour towards risk, a JP production function is used to estimate the influence of production inputs on output risk (Just and Pope 1978; 1979). Thus, the first hypothesis is *"H1: The amount of used production inputs has an influence on output risk"*. To measure farmers' risk attitude, we apply an incentivised HL lottery (Holt and Laury, 2002) within an extra-laboratory experiment. According to Charness et al. (2013: 93), such experiments "have the same spirit as laboratory experiments, but are conducted in a non-standard manner". These methods allow for comparing the HL risk measures with an over- or underuse of production inputs. Through utilization of the JP production function, we can answer the second hypothesis, *"H2: More risk-averse farmers use more risk-reducing and less risk-increasing inputs"*.

The present research contributes to the existing literature in several ways. First, it adds to the discussion regarding the external validity of experimental results to field behaviour (Levitt and List, 2007; Camerer, 2011; Roe and Just, 2009) We are the first that are comparing production decisions evaluated with a JP production function and risk attitude measured with an incentivised HL lottery. Second, in the research area production is focused on rubber and oil palm cultivation. Therefore, output risk of rubber production can cause high income risks for the farmers. Moreover, it is important to know how to manage risk in rubber, because this could raise its attractiveness in comparison to the less environmental friendly oil palm. Thus far, little is known about risk-influencing effects of production inputs in rubber production. However, a deeper understanding of how to influence output risk in rubber production is relevant for the farmers, as well as for society as a whole in the Jambi province.

The remainder of the paper is organised as follows: The methodology is explained in Section 2. Section 3 gives a description of the sample selection and the data, while Section 4 presents and discusses the results. Section 5 concludes.

2. Methods

To answer the hypotheses of this paper, we proceed as follows: In Section 2.1. we explain how we apply a JP production function to analyse the inputs' influence on output risk. In Section 2.2., we explain how we test whether inputs over- or underuses are correlated with farmers' risk attitude measured with a HL lottery and how we evaluate if more risk averse farmers use more risk-reducing and less risk-increasing production inputs.

2.1. Procedure for estimating inputs' influence on output risk

With the JP production function (Just and Pope, 1978; 1979), we want to determine the production inputs' influence on the output risk, i.e., output variance. The model used to determine this is:

$$q_{pv}(x_{kpv}, \varepsilon_{pv}) = f(x_{kpv}) + \varepsilon_{pv}\sqrt{h(x_{kpv})} \tag{1}$$

where q_{pv} represents the production output from plot p in village v. In the used data set, a farmer may have several rubber plots, however, these plots are always within one village. x_{kpv} represents the input k of plot p in village v. What is more, $f(x_{kpv})$ is the function which determines the output level, whereas the function $\sqrt{h(x_{kpv})}$ determines the inputs' influence on output risk, both influenced by the input variables x_{kpv}. ε_{pv} is a stochastic disturbance with an expected value of zero, along with a positive and constant variance.

The estimation strategy used in this study is based on Gardebroek et al. (2010). Following this direction, we define that $\varepsilon_{pv}\sqrt{h(x_{kpv})} = u_{pv}$. Thus, Equation (1) can be rewritten as $q_{pv}(x_{kpv}) = f(x_{kpv}) + u_{pv}$, with u_{pv} as a residual .This modification makes the function for the output level $f(x_{kpv})$ feasible. We apply a quadratic specification since this allows for using zero-value input observations. Thus, $q_{pv}(x_{kpv}) = f(x_{kpv}) + u_{pv}$ is specified by:

$$q_{pv} = \alpha_0 + \alpha_v + \sum_{k=1}^{K} \alpha_k \, x_{kpv} + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{K} \alpha_{kj} x_{kpv} x_{jpv} + u_{pv} \qquad (2)$$

The village specific effects on output level, e.g., through different soil or weather conditions, are captured by α_v. Moreover, α_k and α_{kj} show the inputs' influence on output level. K equals the number of applied input variables. α_0 is the intercept. With a translog specification for u_{pv}, we can estimate inputs' influence on output variance. This translog risk function is given by:

$$ln|u_{pv}| = \beta_0 + \frac{1}{2}\left(\beta_v + \sum_{k=1}^{K} \beta_k ln(x_{kpv}) + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{K} \beta_{kj} ln(x_{kpv}) ln(x_{jpv}) + \sum_{m=1}^{M} \beta_m D_m \right) + w_{pv} \qquad (3)$$

In Equation (3), the dependent variable $|u_{pv}|$ is derived from the absolute value of the residual in Equation (2). β_v covers village-specific fixed effects of production risk. Moreover, since all values are taken in the natural logarithm ln, the coefficients β_k and β_{kj} reflect the elasticities of the output variance for the specific input variable, i.e., the inputs' influence on output risk. Moreover, we have zero-value observations for some of the input variables; thus, M signifies the number of correction dummies which are necessary to estimate unbiased coefficients for such inputs. These dummies contain a value of one for each zero-value observation of the respective variable (Battese, 1997). Other researchers have also applied such a dummy variable technique when using a JP production function (Di Falco and Chavas, 2009). β_0 is the intercept and w_{pv} is the error term. For more in-depth details concerning Equation (3), please refer to the relevant literature (Gardebroek et al., 2010; Just and Pope, 1978; 1979).

For this analysis, we are interested in the marginal risk that is created by each input. In a translog specification such an inputs' marginal effect on risk is calculated as follows (Pavelescu, 2011):

$$\frac{\delta ln|u_{pv}|}{\delta x_{kpv}} = \beta_k + 2\beta_{kk} ln(x_{kpv}) + \sum_{j=1 \neq k}^{K} \beta_{kj} ln(x_{jpv}) \qquad (4)$$

Equation (4) shows the partial derivative of the output risk of an input k. β_k, β_{kk} and β_{kj} are coefficient from Equation (3). With Equation (4), we can calculate the risk-increasing or risk-reducing effect of an input for each observation.

To prove the reliability of the JP production function, we test for monotonicity assumption for the function which determines the output level, i.e., Equation (2). Thus, we test whether inputs' marginal influence on output level is positive. Therefore, we derive Equation (2) as follows:

$$\frac{\delta q_{pv}}{\delta x_{kpv}} = \alpha_k + 2\alpha_{kk} x_{kpv} + \sum_{j=1 \neq k}^{K} \alpha_{kj} x_{jpv} \tag{5}$$

2.2. Procedure for estimating the influence of experimentally measured risk attitude on over- or underuse of inputs

To measure farmers' risk attitude, an HL lottery is conducted (Holt and Laury, 2002). The HL lottery, shown in Table 1, is comprised of ten paired lottery-choice decisions between option A and option B. Each option has two possible payouts which systematically change their probabilities. Option A has a moderate payout-spread and is therefore the "safe choice", whereas option B has a high payout-spread making it the "risky choice". Ex post, one pair is randomly chosen and paid out to the participants. The lottery was adapted to take into consideration that at least some of the people in the rural areas of Sumatra have a limited education or may even be illiterate. Therefore, the experiment was designed by visualising probabilities with differently coloured balls instead of complicated numerical probabilities, which makes the experiment easily understandable (Ihli and Musshoff, 2013). The applied design is pictured in the appendix (Figure A1).

Table 1. Payoffs of the HL lottery

Choice	Option A	Option B	Difference in the expected payoff
1	With 10% price of Rp 4,000 With 90% price of Rp 3,200	With 10% price of Rp 7,600 With 90% price of Rp 200	Rp 2,340
2	With 20% price of Rp 4,000 With 80% price of Rp 3,200	With 20% price of Rp 7,600 With 80% price of Rp 200	Rp 1,680
3	With 30% price of Rp 4,000 With 70% price of Rp 3,200	With 30% price of Rp 7,600 With 70% price of Rp 200	Rp 1,020
4	With 40% price of Rp 4,000 With 60% price of Rp 3,200	With 40% price of Rp 7,600 With 60% price of Rp 200	Rp 360
5	With 50% price of Rp 4,000 With 50% price of Rp 3,200	With 50% price of Rp 7,600 With 50% price of Rp 200	Rp -300
6	With 60% price of Rp 4,000 With 40% price of Rp 3,200	With 60% price of Rp 7,600 With 40% price of Rp 200	Rp -960
7	With 70% price of Rp 4,000 With 30% price of Rp 3,200	With 70% price of Rp 7,600 With 30% price of Rp 200	Rp -1,620
8	With 80% price of Rp 4,000 With 20% price of Rp 3,200	With 80% price of Rp 7,600 With 20% price of Rp 200	Rp -2,280
9	With 90% price of Rp 4,000 With 10% price of Rp 3,200	With 90% price of Rp 7,600 With 10% price of Rp 200	Rp -2,940
10	With 100% price of Rp 4,000 With 0% price of Rp 3,200	With 100% price of Rp 7,600 With 0% price of Rp 200	Rp -3,600

Source: Author's illustration according to Holt and Laury (2002).

Notes: Rp = Indonesian rupiah.

Table 1 shows that as the probability for higher outcomes increases in the HL lottery, the expected payoff difference between option A and option B decreases; beginning with the 5th pair of choices, the expected outcomes become negative. Therefore, a risk neutral participant would switch from option A to option B with the 5th choice. For the first choices, only a strongly risk seeking participant would choose option B, whereas for the final choices, only a strongly risk averse participant would choose option A.

Consistent behaviour would be established if the participant would never switch from option B to option A as they make decisions in the HL lottery. The number of option A choices, i.e., the safe choices, would then be the relevant value which indicates the risk attitude. Unfortunately, such consistent behaviour is not always observed in the HL lottery (Holt and Laury, 2002). In the literature, several methods have been established for managing inconsistent behaviour in the HL lottery. The first method, as discussed by Holt and Laury (2002), is to consider only observations with consistent behaviour for the analysis. The number of safe choices present among the consistent observations is then the respective measure; we will call this measure "HL-consistent". This measure has the disadvantage of losing observations with inconsistent behaviour. Alternatively, Holt and Laury suggest using the total number of safe choices as a risk measure, independent of whether the choices are consistent; this measure will be called "HL-total". Another method is to consider only the observation at the first switching point from option A to option B, independent of whether the choices beyond this point are consistent (Masclet et al., 2009); this measure will be termed "HL-change". With all three of the HL-measures presented here, a higher value implies more risk averse behaviour. For robustness purposes we will apply all three mentioned HL-measures for this analysis.

In order to assess the over- or underuse of a certain input, we deduct the perfect rational, profit maximising input use x_{kpv}^{*} from the real input use x_{kpv}. To calculate the profit maximising input use x_{kpv}^{*}, we have to start with the profit calculation, which is as follows:

$$\pi_{pv} = q\left(x_{kpv}^{*}\right)p_{pv} - \sum_{k=1}^{K} x_{kpv}^{*} w_{kpv} \qquad (6)$$

In Equation (6), the profit π_{pv} is calculated by multiplying output $q\left(x_{kpv}^{*}\right)$ with the product price p_{pv} and deduct the input x_{kpv}^{*} multiplied with an input price of w_{kpv} to account for the input costs. By deviating this equation with respect to x_{kpv}^{*} we get:

$$0 = \frac{\partial q\left(x_{kpv}^{*}\right)}{\partial x_{kpv}^{*}} p_{pv} - \frac{\partial \sum_{k=1}^{K} x_{kpv}^{*}}{\partial x_{kpv}^{*}} w_{kpv} \qquad (7)$$

The derivation on the right side of the minus equals one. Thus, restructuring and implementing the production function, which is also shown in Equation (2), yields:

$$\frac{w_{kpv}}{p_{pv}} = \frac{\partial\left(\alpha_0 + \alpha_v + \sum_{k=1}^{K} \alpha_k x_{kpv}^{*} + \sum_{k=1}^{K} \sum_{j=1}^{K} \alpha_{kj} x_{kpv}^{*} x_{jpv} + u_{pv}\right)}{\partial x_{kpv}^{*}} \qquad (8)$$

By derivation and restructuring of Equation (8) we finally find how to calculate the perfect rational, profit maximising input use x_{kpv}^{*}.

$$x_{kpv}^{*} = \frac{\frac{w_{kpv}}{p_{pv}} - \alpha_k - \sum_{j=1 \neq k}^{K} \alpha_{kj} x_{jpv}}{2\alpha_{kk}} \qquad k = 1, \ldots, K \qquad (9)$$

By applying the coefficients of the function for the output level (Equation (2)), we can calculate the values for x_{kpv}^* for each input and observation. The difference between the real input use x_{kpv} and the perfect rational, profit maximising input use x_{kpv}^* is shown by x_{kpv}^Δ:

$$x_{kpv}^\Delta = x_{kpv} - x_{kpv}^* \qquad\qquad k = 1, \dots, K \qquad (10)$$

Thus, a positive or negative x_{kpv}^Δ identifies the over- or underuse of a certain input, respectively. With the values of x_{kpv}^Δ at hand, it is possible to test whether inputs over- or underuse correlates with producers' risk-aversion HL_{pv} as follow:

$$x_{kpv}^\Delta = \gamma_0 + \gamma_1 HL_{pv} + \gamma_2 (HL_{pv})^2 + z_{kpv} \qquad (11)$$

γ_1 and γ_2 show the influence of the linear and the squared HL-measures on input' over-or underuse. γ_0 and z_{kpv} are the intercept and the residual, respectively. For robustness purposes, all three discussed HL-measures for risk attitude, i.e., HL-consistent, HL-total and HL-change, are used as independent variables for a single variable quadratic function with x_{kpv}^Δ as the dependent variable. Therefore, we have three independent regressions for each input variable. By deriving Equation (11), we can calculate the marginal effect of the HL-measures on input use:

$$\frac{\partial x_{kpv}^\Delta}{\partial HL_{pv}} = \gamma_1 + 2\gamma_2 HL_{kpv} \qquad (12)$$

Equation (12) determines the marginal effects of the respective HL-measure on the input use. Combined with the results from Section 2.1., we can demonstrate if more risk-averse farmers use more risk-reducing and less risk-increasing production inputs.

3. Sample selection and data

The data collection was conducted in the Jambi Province on Sumatra, Indonesia. Jambi has approximately three million inhabitants and has an area of roughly 50,000 square kilometres. The research area extends over five regencies of the Jambi Province: Sarolangun, Tebo, Bungo, Batang Hari and Muaro Jambi. Rubber is a major tree crop in this area (Otsuka et al., 2000).

The data were collected from October to December 2012 in 35 randomly chosen villages. With one exception, 2 villages are always located in one district, resulting in 18 different districts. Depending on the size of each village, between 10 and 24 randomly chosen farmers were invited to participate in this research. Since not all farmers accepted the invitation, and not all farmers cultivate rubber, the final data set consists of 185 farmers. While the production and socioeconomic data were collected a few days in advance, the experiments took place, depending on local conditions, in the early afternoon or after evening prayer. The experiments were conducted in available public spaces such as schools, gymnasiums or the house of the village head. Before the experiment began, participants had to sit separately from one another and were not allowed to speak, except with the enumerators. Each participant then received a questionnaire to fill-in with their experimental decision and an enumerator explained the instructions with the support of visual aids. In order to account for learning effects, the HL lottery was conducted twice. For the analysis, only the results of the second HL lottery were used. To avoid a consecutive execution of these HL lotteries, other experiments were included as an interruption. These experiments tested for, e.g., trust among the participants or dealt with ex ante testing of policy measures and had no direct connection to the HL lottery. To avoid disturbing influences from the first HL lottery or the other experiments on the second HL lottery, all earnings were evaluated after the decisions had been made.

The 185 farmers included in this data set cultivate a combined total of 260 rubber plots. Most participants won between Rp 40,000 and Rp 60,000 for all experiments, which were then distributed in the form of a shopping voucher for a local shop. The two HL lotteries account for Rp 8,336 in average. Considering that the average daily wage for a worker is around Rp 50,000 in the research area, the amount of vouchers seem to be adequate compensation for these experiments. The lotteries took about half an hour, whereas the other experiments took around three hour.

Table 2. Socioeconomic, experimental and production data

	mean	sd
Observations rubber farmers	185	
Male, percent	83.61	
Age, years	44.03	10.49
Education, years	7.67	3.12
Household size, persons	4.50	1.42
First lottery, HL-consistent	3.85	2.95
Second lottery, HL-consistent	3.95	2.72
First lottery, HL-total	4.39	2.42
Second lottery, HL-total	4.36	2.32
First lottery, HL-change	2.46	2.58
Second lottery, HL-change	2.64	2.56
Observations rubber plots	260	
Yield, kg[a)]	3,167	3,441
Fertiliser, kg[a)]	78.2	224.8
Herbicides, litre	5.45	9.79
Labour, hours/year	964	612
Plot size, hectare	2.07	1.84
Plantation age, years	19.30	9.14

Source: Survey data, authors' calculation.

Notes: a) Fertiliser and herbicides have 192 and 138 zero-value observation, respectively.

Table 2 shows the socioeconomic, experimental and production data of the relevant farmers and plots. For this analysis we apply five production inputs, i.e., fertiliser, herbicides, labour, plot size and plantation age. For fertilizer and herbicides, the high standard deviation in relation to mean values can be explained through the high share of zero-value observations. For each of the three HL measures, the differences between the first and the second lotteries are not significant at the 5% level.

4. Results and discussion

In the section 4.1, we show the estimated influence form production inputs on output risk. Thus, we can respond to the first hypotheses. Section 4.2 shows the correlation of the experimentally measured risk attitude and the input use. Together with results from 4.1, the second hypotheses is answered.

4.1. Estimated inputs' influence on output risk

Following the estimation strategy described in Section 2.1, the JP production function starts with estimating inputs' influence on output level with the quadratic production function, described in Equation (2). Therefore, we account for five production inputs, i.e., fertiliser, herbicides, labour, plot size and plantation age. We assume that output variance is related to input use, which implies heteroskedasticity. Therefore, we apply White's procedure in order to obtain robust standard errors (Wooldridge, 2002). The results of this estimation can be seen in Table A1 in the appendix. Seven out of the twenty estimated coefficients are significantly different from zero at a 10% level. An F-test clearly indicates the existence of unobserved, village constant effects. Moreover, the adjusted R-square of 0.617 indicates a high degree of explanatory power of the estimated production function.

For each input of this quadratic production function, we tested whether the monotonicity assumption is violated. Therefore, we calculated the marginal influence on output level for each production input (Equation (3)). In 25 of the 68 observations where fertilizer is used, monotonicity is violated. However, if we split those 68 observations into herbicide users and non-herbicide users, we find that fertiliser users which also use herbicide violate monotonicity at a higher level of 44.2% (23/52 observations), whereas fertilizer users that do not also use herbicide do this only at a reasonable level of 12.5% (2/16 observations). For herbicide, 47 out of 122 observations where herbicide is used violate the assumption of monotonicity. However, if we split these 122 observations up into fertiliser users and non-fertiliser users, we find that 67.3% (35/52) and 17.1% (12/70) violate monotonicity, respectively. For the majority of the 52 plots where the use of fertilizer and herbicides is combined, monotonicity is violated, whereas for the other plots the monotonicity assumption for fertiliser and herbicide is fulfilled at a reasonable level. Through further investigation, we found that those 52 plots have on average 72.8 kg more yield per hectare and also a 2.5% higher product price. Even though these differences are not significant, farmers seem to have an advantage in using both of these inputs, even though the violation of monotonicity indicates an overuse of these inputs in many cases. Moreover, other effects of input use, e.g., on output risk, might explain the overuse of inputs. However, for labour and plot size, we found that monotonicity was violated at a reasonable level in 3.5% (9/260) and 10.4% (27/260) of the observations, respectively. Since we do not expect yields to increase with plantation age, the violation in 39.2 % (102/260) of the observations is unproblematic for this production input. To summarize, aside from the observations where fertiliser and herbicide are used simultaneously, monotonicity is fulfilled to a reasonable degree. Therefore, it is apparent that we have a well-specified production function.

To estimate inputs' influence on output risk, we apply the translog risk function shown in Equation (3). By including fixed effects, we account for village constant, risk influencing effects. In order to obtain unbiased results, we introduced three correction dummies: one for fertiliser, one for herbicides and due to the significant interaction found between fertilizer and herbicide usage in the discussion about monotonicity, we additionally introduce a correction dummy for observations with non-zero values of fertilizer and herbicides (Battese, 1997). As demanded by the model, all variables are applied in logarithmic values (Just and Pope 1978; 1979). The results of this estimation can be seen in Table 3.

Table 3. Elasticities of input use on risk with translog estimation

	mean	se	p-value	
Fertiliser	0.636	2.223	0.775	
Herbicides	-1.073	1.759	0.542	
Labour	1.449	4.464	0.746	
Plot size	5.902	3.676	0.110	
Plantation age	-0.635	6.362	0.921	
Fertiliser x Fertiliser	-0.021	0.095	0.827	
Fertiliser x Herbicides	-0.006	0.018	0.725	
Fertiliser x Labour	-0.045	0.037	0.219	
Fertiliser x Plot size	0.037	0.032	0.247	
Fertiliser x Plantation age	0.002	0.030	0.933	
Herbicides x Herbicides	0.016	0.097	0.872	
Herbicides x Labour	0.132	0.038	0.001	***
Herbicides x Plot size	-0.103	0.036	0.004	***
Herbicides x Plantation age	-0.012	0.038	0.747	
Labour x Labour	-0.168	0.164	0.308	
Labour x Plot size	-0.052	0.268	0.846	
Labour x Plantation age	0.298	0.289	0.304	
Plot size x Plot size	0.143	0.141	0.309	
Plot size x Plantation age	-0.672	0.261	0.011	**
Plantation age x Plantation age	0.083	0.261	0.750	
Dummy fertiliser	*0.396*	*13.275*	*0.976*	
Dummy herbicides	*-0.566*	*8.024*	*0.944*	
Dummy fertiliser x Dummy herbicides	*0.281*	*1.974*	*0.887*	
Constant	-21.38	44.97	0.635	
Observations	260			
Adjusted R-square	0.623			

Source: Authors' computation.

Notes: Significantly different from zero at the **5% and ***1% levels.

In Table 3, from the 20 variables which are not correction dummies, 3 are significantly different from zero at a 5% level. However, since the high adjusted R-square of 0.623 indicates a high explanatory power, this regression seems to be a good basis for the further analysis. An F-test indicates the existence of unobserved, village constant effects on the output risk. By further investigating these effects, we found that approximately 10.8% of the variation between villages can be explained with regency variables. Thus, the south-western regency, Sarolangun, has the highest output risk, whereas the north-western Tebo and Bungo have medium output risk. The lowest output risk was found in Batang Hari, which is in the central region of the research area, followed by the eastern regency Muara Jambi. It can thus be determined that there are regional differences concerning the output risk.

With respect to the first hypothesis *"H1: The amount of used production inputs has an influence on output risk"* Table 3 shows that 3 out of 20 combinations of inputs have a significant influence on output risk. This low share of significant influences for such regressions can also be found in other studies, e.g., 4 out of 35 (Gardebroek et al., 2010). Moreover, the adjusted R-square of 0.623 shows that we can explain much of the output risk with the used inputs. Therefore, we accept the first hypothesis.

To determine the inputs' marginal influence on output risk, we apply Equation (5). For fertiliser and herbicides, it is reasonable to consider only observations with non-zero-values. For the purpose of this article, we are primarily interested in the direction, and not in the size, of an inputs' influence on output risk. To find such direction, we compare the number of risk-increasing and risk-reducing observations for each input. However, it is difficult to determine at which proportion of risk-increasing and risk-reducing observations an input's influence on output risk is distinct. In order to determine the direction of inputs' influence on output risk, we determined that it is sufficient if more than 75% of the observations point in the same direction.

Table 4. Marginal effects of inputs on output risk

Input	Non-zero observations	Risk-increasing observations	Risk-decreasing observations	Inputs' influence on risk
Fertiliser	68	0 (0%)	68 (100%)	Risk-decreasing
Herbicides	122	114 (93%)	8 (7%)	Risk-increasing
Labour	260	106 (41%)	154 (59%)	Ambiguous
Plot size	260	197 (76%)	63 (24%)	Risk-increasing
Plantation age	260	145 (56%)	115 (44%)	Ambiguous

Source: Authors' computation.

Table 4 shows that for all 68 non-zero observations, the marginal effect of fertiliser usage is risk-decreasing. Moreover, the marginal effect of herbicide usage is risk-increasing for a clear majority (93%) of the non-zero-value observations. For plot size, we found a risk-increasing effect for 76% of the observations. Therefore, we consider this production input to also be risk-increasing.

However, for labour and plantation age the observations of risk-increasing and risk-decreasing marginal effects are almost equal, making the influence on output risk ambiguous. Thus, to go further with the analysis only fertilizer, herbicides and plot size are taken into consideration.

4.2. Influence of experimentally measured risk attitude on input use

According to Equation (10), x_{kpv}^{Δ} indicates an over- or underuse of an input, respectively. For fertiliser, we found an overuse in 40 and an underuse in 28 observations. For herbicides, we found an over- or underuse in 74 and 48 observations, respectively. This relatively high share of overuse was already established for both of these inputs during the discussion about the monotonicity assumption. Unfortunately, for the plot size input, we have little information pertaining to land prices. Therefore, a reasonable calculation of x_{kpv}^{Δ} is not possible and we have to omit this input for the further analysis.

Table 5. Effect of HL-measures on fertiliser and herbicide over- or underuse (x_{kpv}^{Δ})[a)]

	Estimated influence of the respective HL-measure on over- or underuse of input (Equation (11))				**Marginal effect of the respective HL-measure on over- or underuse of input** (Equation (12))	
	linear (γ_1)		**squared** (γ_2)		$\frac{\partial q(x_{kpv}^{\Delta})}{\partial HL_{kpv}} > 0$ **(positiv marginal effect)**	$\frac{\partial q(x_{kpv}^{\Delta})}{\partial HL_{kpv}} < 0$ **(negativ marginal effect)**
	mean	**p-value**	**mean**	**p-value**		
x_{kpv}^{Δ} **fertiliser**						
HL_{pv}-consistent[b) c)]	-272.2	0.025**	24.940	0.051*	78.0% (32/41)[d)]	22.0% (9/41)[d)]
HL_{pv}-total[b)]	-154.0	0.115	9.865	0.338	85.3% (58/68)[d)]	14.7% (10/68)[d)]
HL_{pv}-change[b)]	-197.9	0.008***	19.25	0.036**	55.9% (38/68)[d)]	44.1% (30/68)[d)]
x_{kpv}^{Δ} **herbicides**						
HL_{pv}-consistent[b) c)]	4.510	0.034**	-0.629	0.017**	21.3% (16/75)[d)]	78.7% (59/75)[d)]
HL_{pv}-total[b)]	2.469	0.142	-0.287	0.144	21.3% (26/122)[d)]	78.7% (96/122)[d)]
HL_{pv}-change[b)]	3.484	0.021**	-0.516	0.011**	36.9% (45/122)[d)]	63.1% (77/122)[d)]

Source: Authors' computation.

Note: Significantly different from zero at the *10%, **5% and ***1% levels. a) Estimating with fixed effects at the district level, as well as at the village level, results in qualitatively similar results, but in high losses of degrees of freedom. Moreover, estimating with the HL-measures from the first HL-lottery leads to similar results. b) Each line represents estimation results of one regression. c) Lost observations through inconsistency are 27 and 47 for fertiliser and herbicides, respectively. d) Share of observations with the respective marginal effect.

Table 5 shows the influence of the HL risk measures on over- or underuse of fertiliser and herbicides. Therefore, the regression results from Equation (11) regarding fertiliser and herbicides are presented, each with results for HL-consistent, HL-total and HL-change. A higher HL-measure indicates a farmer having a higher aversion to risk. Moreover, the respective marginal effect of these HL-measures on x_{kpv}^{Δ} is calculated (Equation (12)). Similar to Table 4, the effect is determined to be definite if more than 75% of the observations point in one direction. Before interpreting Table 5, it is necessary to recall that fertiliser was found to be risk-decreasing while herbicide was found to be risk-increasing (Table 4).

For the three regressions with x_{kpv}^{Δ} fertiliser as the dependent variable, we found that the coefficients of HL-consistent and HL-change are significant different from zero at 5% or close to this level, which strongly indicates a relationship between these HL-measures and fertilizer use. For HL-total, no significant difference from zero is indicated. For HL-total and HL-consistent, more than 75% of the observations clearly indicate a positive marginal effect of these HL-measures on x_{kpv}^{Δ} fertiliser. Despite the ambiguous marginal effect for HL-change, we can clearly support the statement that more risk-averse farmers (indicated by higher HL-measures) use more (risk-decreasing) fertiliser. Thus, for the fertiliser input we find consistent results for input use and experimentally measured risk-aversion.

For x_{kpv}^{Δ} herbicides, we found a pattern similar to the outcome for fertilizer. Whereas the coefficients of HL-total are not significantly different from zero, the coefficients of HL-consistent and HL-change are significant at 5% level. This clearly indicates a relationship between the latter two HL-measures and x_{kpv}^{Δ} herbicides. For HL-consistent and HL-total, a negative marginal effect on herbicides use for more than 75% of the observations can be seen. For HL-change, with a share of 63.1%, the marginal effect is ambiguous. Overall, results strongly indicate that more risk-averse farmers use less (risk increasing) herbicide. This indicates consistent results for herbicides use and experimentally measured risk-aversion.

With respect to the second hypothesis *"H2: More risk-averse farmers use more risk-decreasing and less risk-increasing inputs"*, we find that more risk averse farmers use more risk-decreasing fertilizer and less risk-increasing herbicides. Consequently, we accept hypothesis two. It seems that participants' field behaviour towards risk and their experimentally measured risk attitude are consistent considering the example of using risk-influencing production inputs. In other words, for the context of this article we found that the experimentally measured risk attitude has external validity in the field.

5. Conclusions

Production output in agriculture can vary significantly, making farming a risky business. Literature indicates that such output risks can be influenced by the choice of production inputs. However, these output risks combined with farmers' risk attitudes, influence farmers' production decisions. Having a better understanding of farmers' risk attitude can help with better understanding farmers' production decisions, especially with respect to output risk and, thus, in better dealing with changing circumstances. This is relevant for the individual farmers, as well as for the development of proper policy measures. This research is done for the case of rubber farmers on Sumatra, which is an important region for rubber production in Indonesia. The output risk of rubber is especially relevant for the research area, since in large parts of the area rubber is the main tree crop and therefore plays a major role in income generation for farmers.

To investigate the research hypotheses, i.e., *"H1: The amount of used production inputs has an influence on output risk"* and *"H2: More risk-averse farmers use more risk-reducing and less risk-increasing inputs"*, a JP production function was conducted to determine inputs' influence on output risk. Furthermore, a HL lottery was used to experimentally measure farmers' risk attitudes. We find that fertiliser is a risk-decreasing input, whereas herbicides and plot size are risk-increasing production inputs. For labour and plantation age, the influences on output risk are ambiguous. In accordance with our expectations, we found that more risk averse farmers use more fertiliser (risk-decreasing) and less herbicides (risk-increasing). These results indicate that the use of inputs, with respect to inputs' influence on output risk, and the experimentally measured risk attitude are consistent.

In the literature, the relationship between field decisions regarding risk and experimentally measured risk attitude is unclear. Some articles show no significant or inconsistent correlations of field behaviour and experimentally measured risk attitude, (e.g., Anderson and Mellor, 2009; Barham et al., 2012; Hellerstein et al., 2013), while other articles indicate consistent correlations (e.g., Engle-Warnick et al., 2007; Hill, 2009). However, this discussion demands for further contributions. Future research could be an extension to other crops, an evaluation of a farm as a whole, or to other countries. Applying the method in this article to a panel data set could account for possible changes over time which would further support the discussion of external validity of experimental results. Additionally, Lence (2009) discuss difficulties of insufficiently estimating the risk aversion in combination with a JP production function. In this context, it could be interesting to compare the estimated with the measured risk attitude.

The results of this article are relevant for several reasons. First, by comparing the results of a JP production function and risk attitude measured with an incentivised HL lottery, we add this example to the literature for testing the external validity of such experimental results. This is relevant because influencing output risk with the input choice is something that can be done by a vast majority of farmer. Second, we found significant influence from fertiliser and herbicides usage on output risk for rubber production in the research area. Moreover, the use of these inputs goes along with farmer risk attitude. This knowledge can help with managing such risks and provides important information for farmers, as well as for policy decision makers. The massive expansion of oil palm plantations in the research area causes considerable negative externalities (Koh and Wilcove, 2008; Wilcove and Koh, 2010; Laumonier et al., 2010). Since rubber is the obvious alternative to oil palm, inreasing the attractiveness of rubber by knowing how to handle output risk may lead to a conversion to this fruit, which would reduce the mentioned negative externalities.

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Appendix

Table A1. Quadratic production function in levels

	mean	se[a)]	p-value
Fertilizer	-1.790	2.401	0.461
Herbicides	85.609	58.363	0.152
Labour	1.426	1.034	0.177
Plot size	353.718	514.561	0.496
Plantation age	114.081	74.687	0.136
Fertilizer x Fertilizer	0.006	0.002	0.003***
Fertilizer x Herbicides	-0.613	0.136	0.000***
Fertilizer x Labour	-0.003	0.001	0.073*
Fertilizer x Plot size	0.711	0.561	0.214
Fertilizer x Plantation age	0.350	0.168	0.044**
Herbicides x Herbicides	6.621	1.330	0.000***
Herbicides x Labour	0.045	0.065	0.494
Herbicides x Plot size	-39.571	22.705	0.090*
Herbicides x Plantation age	-5.764	3.506	0.109
Labour x Labour	0.000	0.001	0.602
Labour x Plot size	-0.051	0.312	0.872
Labour x Plantation age	-0.037	0.061	0.545
Plot size x Plot size	-14.006	14.201	0.331
Plot size x Plantation age	152.995	41.215	0.001***
Plantation age x Plantation age	-1.157	0.983	0.248
Constant	-868.405	1066.931	0.421
Observations	260		
Adjusted R-square	0.617		

Source: Authors' computation.

Notes: Significantly different from zero at the *10%, **5% and ***1% levels. a) Heteroscedasticity robust standard errors.

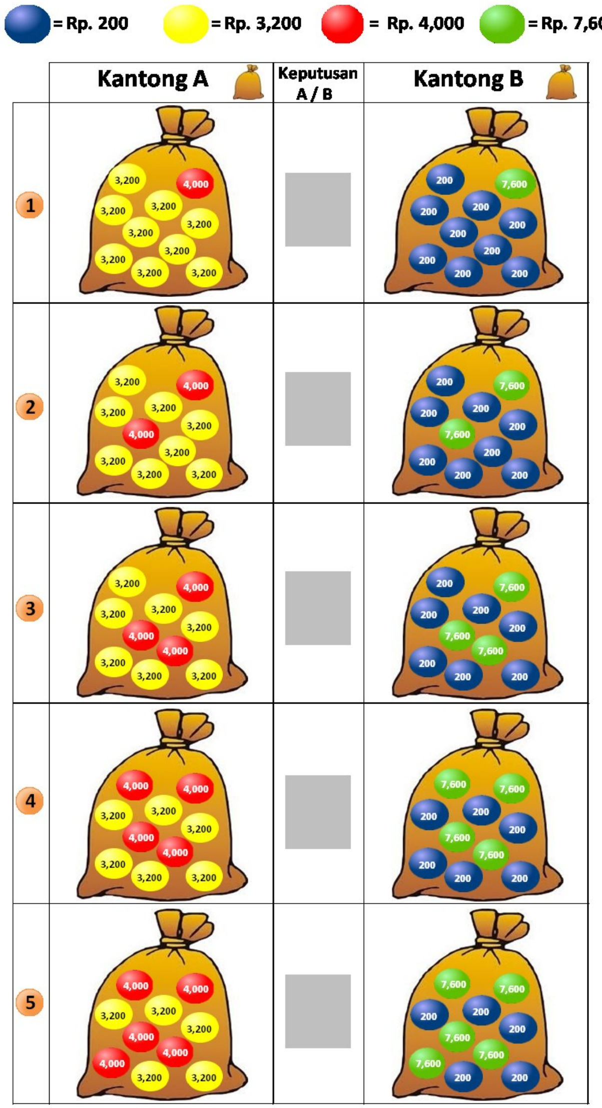

Figure A1. HL lottery, part 1

Source: Author's illustration following Ihli und Musshoff (2013).

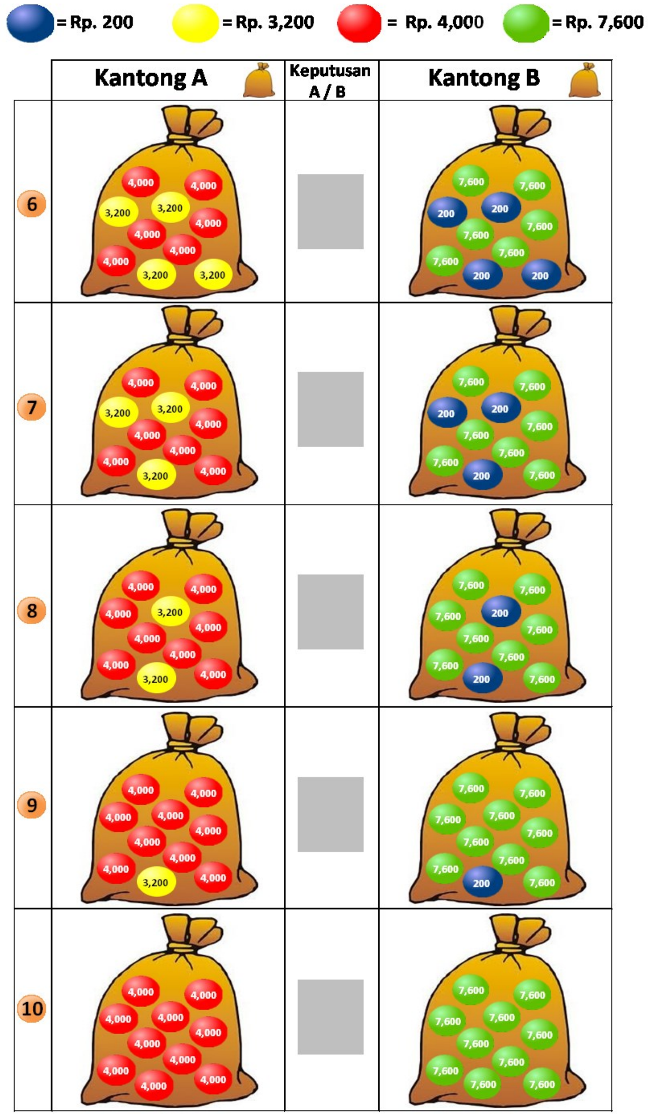

Figure A1 continued. HL lottery, part 2

Source: Author's illustration following Ihli und Musshoff (2013).