Comparing the Use of Risk-influencing Production Inputs and Experimentally Measured Risk Attitude: Do the 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, a Just-Pope production function indicates production inputs' influence on output risk, and a Holt-Laury lottery is used to measure farmers' risk attitudes. We then test whether more risk averse farmers use more risk-reducing and less risk-increasing production inputs. To do so, a unique data set which includes 185 small-scale rubber farmers on the island of Sumatra, Indonesia, is used. The Just-Pope production function suggests that higher fertiliser usage has a risk-reducing effect, whereas higher herbicide usage has a risk-increasing effect. Comparing this with the outcome of a Holt-Laury lottery, we found that more risk averse farmers use more fertiliser (risk-reducing) and less herbicides (risk-increasing). The consistency of these results can be interpreted as reinforcing the external validity of measuring risk attitude with a Holt-Laury lottery.

Key Words

Holt-Laury lottery; Just-Pope production function; output risk; rubber; Indonesia

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 farmers' income, thus making farming a risky business (KEY and MACDONALD, 2006). Such output risks, in combination with the risk attitudes of farmers, are among the main drivers for production decisions in agriculture (CHAVAS et al., 2010). In this context, HELLERSTEIN et al. (2013) discuss the importance of understanding the risk attitude/production decision relationship and how it helps with the development of policies which can accommodate changing economic and environmental circumstances, as well as encouraging farmers to make appropriate reactions. However, the precise manner in which risk and risk attitude affect farmers' production decisions is not easy to determine (JUST, 2001; JUST and POPE, 2003).

Analysing output risk as well as risk attitude is a primary focus in the field of research that pertains to risk in agriculture (CHAVAS et al., 2010). An often applied and well-accepted method of investigating output risk, i.e. output variance, in agricultural production, was developed by JUST and POPE (1978; 1979).[1] This method shows production inputs' simultaneous influence on the output level and output variance. Several studies have applied and extended this approach for various contexts and purposes, thus proving its relevance (ANTLE and GOODGER, 1984; CHAVAS and HOLT, 1996; BAR-SHIRA et al., 1997; KUMBHAKAR, 2001; 2002a; 2002b; ABDULKADRI, 2003; ISIK and KHANNA, 2003; KUMBHAKAR and TVETERÅS, 2003; BARRETT et al., 2004; DI FALCO and CHAVAS, 2009; GARDEBROEK et al., 2010; TIEDEMANN and LATACZ-LOHMANN, 2013). Experiments have been a long-proven method for measuring risk attitude (BINSWANGER, 1980). Moreover, HOLT and LAURY (2002) developed a well-accepted experimental method for measuring risk attitude, which is considered to be the "gold standard" of risk attitude measures (ANDERSON and MELLOR, 2008). IHLI and MUßHOFF (2013) further adapted this Holt-Laury (HL) risk attitude measure, to be applied to people with a limited level of formal education. By taking this adaptation into consideration this method can be applied for measuring risk attitudes in rural areas of developing countries.

In the literature a discussion regarding the external validity, sometimes referred to as generalisability (CAMERER, 2011), of experimentally obtained results to field behaviour, is in progress. We denote external validity of experimental results as understanding gained in the lab that "can be extrapolated to the world beyond" (LEVITT and LIST, 2007: 153). Thus, field behaviour is defined as behaviour that occurs

[1] In this article, output variance and output risk will be used interchangeably.

outside of the laboratory. There are few investigations comparing field decisions regarding risk and experimentally measured risk attitudes. HELLERSTEIN et al. (2013) predicts farming decisions related to either diversified operations or having crop insurance with a lottery-choice mechanism that measures farmers' risk attitudes and found contradicting results between field and experimental decisions. Additional examples where lottery choices are used to predict decisions which include risk in agriculture production are crop diversification in Peru, where experimental results helped predict field behaviour (ENGLE-WARNICK et al., 2007); decisions regarding coffee production in Uganda, where the stated risk attitude explained production decisions (VARGAS HILL, 2009); and adoption habits with regards to genetically modified crops in the USA, where BARHAM et al. (2014) distinguishes between ambiguity and risk aversion and results show only a minimal effect related to risk aversion. With respect to non-agricultural decisions ANDERSON and MELLOR (2009) found consistent relationships between experimentally measured risk attitudes and decisions regarding health and safety. However, for agricultural production it is noteworthy in the mentioned articles that predictive power is found in emerging economies (ENGLE-WARNICK et al., 2007; VARGAS HILL, 2009), while little or no predictive power is found in industrialised countries (BARHAM et al., 2014; HELLERSTEIN et al., 2013). It seems that currently no definite answer has been determined as to whether experimentally measured risk attitude is reflected in field behaviour. Further investigations are required in order to provide more examples which directly compare experimental results and field behaviour.

Evaluating farmers' production decisions is a good option for measuring farmers' behaviour towards output risks (JUST and POPE, 1978; 1979) which reflects greatly on farmers' income. By comparing such field behaviour towards risk with an experimentally measured risk attitude, it can be determined if results found in the experiment have external validity to behaviour in the field. 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 the output variance is a direct measure of risk, whereas insurance plans or production diversification are reactions to risk that are strongly influenced by individual preferences. Moreover, influencing the output risk through variations in input use, is a tool which practically every farmer can utilize. Thus, farmers can manage income risk, independent of the availability of other tools such as insurance, production diversification or off-farm income.

On the islands of Sumatra and West Kalimantan, 72% of the Indonesian rubber output is produced (ARIFIN, 2005). The Jambi province on Sumatra, specifically, is a region where rubber is a major crop tree and when combined with oil palm, generates the majority of farmers' income. In this province, 52% of the workforce is employed in the agricultural sector, and approximately half of the cultivated land is used for rubber production, which is typically managed by small-scale farmers (STATISTICAL YEAR BOOK OF ESTATE CROPS, 2012). This shows the economic relevance of rubber production for the region. 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 their risk attitude as measured in an experiment. We test this for the case of small-scale rubber farmers in the Jambi province on Sumatra, Indonesia. To determine farmers' field behaviour towards risk, a JP production function is used to estimate production inputs' influence on output variance (JUST and POPE, 1978; 1979). Thus, the first hypothesis is *"H1: The intensity of used production inputs has an influence on output variance"*. 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". By combining the results of the JP production function and the HL lottery, 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; ROE and JUST, 2009; CAMERER, 2011). We are the first that compare production decisions that are evaluated with a JP production function and risk attitude measured using an incentivised HL lottery. Second, agricultural production is focused on rubber and oil palm cultivation within the research area. It is known that output risk in rubber production may potentially cause high income risks for farmers; furthermore, little is presently known regarding the risk-influencing effects of production inputs in rubber production. Moreover, it is important to determine the best way to manage risk in rubber production, as it could raise its attractiveness in comparison to the less environmental friendly oil palm production (see e.g., KOH and WILCOVE, 2008; LAUMONIER et al., 2010; WILCOVE and KOH, 2010). Thus, a deeper understanding of methods of influencing output risk in rubber production is relevant for farmers, as well as for the general population 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 estimate the inputs' influence on output variance. In Section 2.2, we explain how we test whether inputs over- or underuses[2] are correlated with farmers' risk attitude as measured with a HL lottery. Based on that, 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 Variance

With the JP production function (JUST and POPE, 1978; 1979) we want to determine the production inputs' influence on the 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 and x_{kpv} represents the input k of plot p in village v. Additionally, $f(x_{kpv})$ is the function which determines the output level, whereas the function $\sqrt{h(x_{kpv})}$ determines the inputs' influence on output variance, both influenced by the input variables x_{kpv}. Moreover, 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). Thus, we define that with $\varepsilon_{pv}\sqrt{h(x_{kpv})} = u_{pv}$. By doing so, 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 including village specific effects which allows for using zero-value input observations. Consequently, the function which determines the output level $q_{pv}(x_{kpv}) = f(x_{kpv}) + u_{pv}$ is specified by:

$$\begin{aligned} q_{pv} = \alpha_0 + \alpha_v + \textstyle\sum_{k=1}^{K} \alpha_k\, x_{kpv} + \\ \tfrac{1}{2}\textstyle\sum_{k=1}^{K}\sum_{j=1}^{K} \alpha_{kj} x_{kpv} x_{jpv} + u_{pv} \end{aligned} \tag{2}$$

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 and α_0 is the intercept. With a translog specification, we can estimate inputs' influence on output variance. This translog variance function is given by:

$$\begin{aligned} ln|u_{pv}| = \beta_0 + \tfrac{1}{2}\Big(\beta_v + \textstyle\sum_{k=1}^{K} \beta_k ln(x_{kpv}) + \\ \tfrac{1}{2}\textstyle\sum_{k=1}^{K}\sum_{j=1}^{K} \beta_{kj} ln(x_{kpv}) ln(x_{jpv}) + \\ \textstyle\sum_{m=1}^{M} \beta_m D_m\Big) + w_{pv} \end{aligned} \tag{3}$$

In Equation (3) the dependent variable $ln|u_{pv}|$ is derived from the logarithmic absolute value of the residual from Equation (2). β_v covers village specific fixed effects of production variance. Moreover, since all values are taken in their 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 variance. Furthermore, 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 input variable. This approach is favourable when the share of zero-value observations is significant (BATTESE, 1997). Other researchers have applied similar dummy variable techniques when using JP production functions with a considerable proportion of zero-value observations for fertiliser or manure (DI FALCO and CHAVAS, 2009; 2012; VILLANO and

[2] In comparison to the perfect rational, expected profit maximising input use.

FLEMING, 2006), or solving such problems implicitly (KATO et al., 2011; HOLST, 2013). Additionally, this approach is broadly used within (RAO et al., 2012; BATTESE et al., 1996) or outside (SCHNEIDER, 2005; DEININGER and JIN, 2008; KEIL et al., 2008; IRAIZOZ et al., 2005) the field of agricultural economics. β_0 is the intercept and w_{pv} is the error term. For more in-depth details concerning Equation (3) or the JP production function, please refer to the relevant literature (JUST and POPE, 1978; 1979; GARDEBROEK et al., 2010).

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

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

$$k = 1, \dots, K$$

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

2.2 Procedure for Estimating the Correlation of Experimentally Measured Risk Attitude on Over- or Underuse of Inputs

To measure farmers' risk attitude, a 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 for which the probabilities are systematically changed. 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 level of formal 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 for all participants (IHLI and MUßHOFF, 2013). The applied design is depicted in the appendix (Figure A1).

Table 1 shows that as the probability for higher outcomes in the HL lottery increases, the expected payoff difference between option A and option B decreases; beginning with the 5th pair of choices, the

Table 1. Payoffs in the HL lottery

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

Note: Rp = Indonesian rupiah
Source: HOLT and LAURY (2002)

expected outcome differences become negative. Therefore, a perfect rational, profit maximising participant would switch from option A to option B with the 5th choice. Only a strongly risk seeking participant would choose option B for the first choices, whereas only a strongly risk averse participant would choose option A for the final choices. Additionally, option B is the only rational choice for the 10th pair, thus this choice can be seen as a plausibility test.

Consistent behaviour would be established if the participant switches one time from option A to option B or would never switch from option B to option A as they progress through 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, 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 which display inconsistent behaviour. Alternatively, HOLT and LAURY (2002) suggest using the total number of safe choices as a risk attitude measure, independent of whether the choices are consistent, this measure will be called "HL-total". Another method, which is also discussed in the literature, is to consider 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 will be interpreted as more a risk averse attitude. However, as shown in HOLT and LAURY'S article (2002), the payment amount influences the degree of risk aversion in such a lottery. Therefore, the measured risk aversion is considered to be relative, i.e. relevant for comparing participants with one another, while not being seen as a measurement for absolute risk aversion. 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 expected profit maximising input use x_{kpv}^* from the real input use x_{kpv}. To calculate the expected profit maximising input use x_{kpv}^*, we begin with the expected profit calculation on plot level, which is denoted as follows:

$$\pi_{pv} = q\left(x_{kpv}^*\right)p_{pv} - \sum_{k=1}^{K} x_{kpv}^* w_{kpv} \tag{5}$$

In Equation (5) the expected profit for each plot π_{pv} is calculated by multiplying the output $q\left(x_{kpv}^*\right)$ by the product price p_{pv} and deducting the input x_{kpv}^* multiplied by an input price of w_{kpv} to account for the input costs. By taking the derivative of this equation with respect to x_{kpv}^*, we get the expected marginal value product, which equals to the input price:

$$0 = \frac{\partial q(x_{kpv}^*)}{\partial x_{kpv}^*} p_{pv} - \frac{\partial \sum_{k=1}^{K} x_{kpv}^*}{\partial x_{kpv}^*} w_{kpv} \tag{6}$$
$$k = 1, \dots, K$$

The derivation on the right side of the minus sign equals one. Thus, restructuring and inserting the production function as shown in Equation (2) yields:

$$\frac{w_{kpv}}{p_{pv}} = \frac{\partial\left(\alpha_0+\alpha_v+\sum_{k=1}^{K}\alpha_k x_{kpv}^*+\sum_{k=1}^{K}\sum_{j=1}^{K}\alpha_{kj}x_{kpv}^* x_{jpv}+u_{pv}\right)}{\partial x_{kpv}^*} \tag{7}$$
$$k = 1, \dots, K$$

Through the derivation and restructuring of Equation (7) we determine the calculation for the perfect rational, expected profit maximising input use x_{kpv}^*.

$$x_{kpv}^* = \frac{\frac{w_{kpv}}{p_{pv}} - \alpha_k - \sum_{j=1\neq k}^{K}\alpha_{kj}x_{jpv}}{2\alpha_{kk}} \tag{8}$$
$$k = 1, \dots, K$$

Apparently, we cannot know the optimal input use for x_{jpv} before calculating x_{kpv}^* for any given input. Thus, Equation (8) reveals only a conditional optimisation given the input levels and is, therefore, an approximation of the 'true' optimal input use. By applying the coefficients of the function that determines the output level, i.e. 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 expected profit maximising input use x_{kpv}^* is shown by x_{kpv}^{Δ}:

$$x_{kpv}^{\Delta} = x_{kpv} - x_{kpv}^* \tag{9}$$

Thus, a positive or negative x_{kpv}^{Δ} identifies the over- or underuse of a certain input, respectively. In the case that an inputs' observed value is zero, it is left out of further analysis. 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_i, with subscript *i* indicating each farmer, as follows:

$$x_{kpv}^{\Delta} = \gamma_0 + \gamma_1 HL_i + \gamma_2 (HL_i)^2 + z_{kpv} \tag{10}$$

HL_i is measured on an arbitrary scale from 0 to 10. Since this is experimental data, the form of the relationship with non-experimental data, i.e. the production decisions, cannot be foreseen. Thus, we test both a linear and a quadratic functional form. The latter is illustrated in Equation (10). γ_1 and γ_2 show the influence of the linear and the squared HL-measures on inputs' 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 taking the derivative of Equation (10), we can calculate the marginal effect of the HL-measures on input use:

$$\frac{\partial x_{kpv}^{\Delta}}{\partial HL_i} = \gamma_1 + 2\gamma_2 HL_i \tag{11}$$

Equation (11) determines the marginal effects of the respective HL-measure on input use. Therefore, it is determined whether the input use is correlated with the HL-measures. Combined with the results from the JP production function, as described in 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 was collected 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. Next to oil palm, rubber is a major tree crop in this area (OTSUKA et al., 2000; STATISTICAL YEAR BOOK OF ESTATE CROPS, 2012) and has a long tradition.

The main task in cultivating rubber is tapping, i.e. harvesting. During that process a thin layer of bark is cut with a special knife, so the rubber can drop into a small cup. Simultaneously, the rubber from the previous tapping is collected. This is done twice a week with each rubber tree. Another major task is weed control which is done with herbicides or by mowing. The primary function of herbicide use is to reduce work effort rather than for regulating yield security. Occasionally farmers use fertiliser whereas pesticides are only used as an exception. No heavy machinery is needed for these tasks or other work processes, making rubber crop a labour-intensive crop.

The data was collected from October to December 2012 in 35 randomly chosen villages. Depending on the size of each village, between 10 and 24 randomly chosen farmers were invited to participate in this research. The production data for those farmers was collected a few days in advance by other researchers (DRESCHER et al., 2016; EULER et al., 2016), whereas the socioeconomic data was collected the same day by another research group (GATTO et al., 2015). Since not all farmers showed up for the experiments and not all farmers cultivate rubber, the final data set consists of 185 farmers which cultivate a combined total of 260 rubber plots. Due to time constraints, it was not possible to replace farmers who did not show up for the experiments on short notice. In the used data set, a farmer may hold several rubber plots, these plots, however, are always within one village. 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 were required 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. Posters, similar to Figure A1. in the appendix, were used to illustrate the lottery to the farmers. It was explained that there would be a shopping voucher as a prize and that the amount depends on the farmers' behaviour. We explained that the lottery consists of 10 choice-pairs and that they would have to choose one bag for each of them. Furthermore, we told them explicitly to choose very carefully, since they are only allowed to draw one ball from the bag from a randomly chosen choice-pair.

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 trust between the participants, or dealt with ex ante testing of policy measures, and had no direct connection to the HL lottery. To avoid distorting influences from the first HL lottery, and the other experiments on the second HL lottery, all earnings were evaluated after the decisions had been made.[3]

Most participants won between Rp 40,000 and Rp 60,000 for their participation in all experiments, which were then distributed in the form of a shopping voucher for a local shop. The two HL lotteries account for an average of Rp 8,336. Considering that the average daily wage for a worker is around Rp 50,000 in the research area, the amount given in vouchers seems to be adequate compensation for participation in these experiments. The lotteries took approximately half an hour, whereas the other experiments took around three hours.

It is evident that some farmers in the observation have more than one plot. Thus, it is difficult to interpret a farmers' behaviour when he has several plots, but treats them differently. This is relevant for 54 of the farmers, who are cultivating 129 plots. In the dataset, 37 plots are from farmers who use fertiliser for more than one plot. By taking a closer look, we find only four cases where the difference in fertiliser use per hectare between such plots at farm-level, is more than 10%, whereas these differences on village level vary more substantially. For herbicides, of the 61 plots from farmers, who use herbicides on more than one plot, only 4 plots deviate from the farm average at more than 10%, whereas the differences within the farms of the same village are enormous. For labour use, only for 8 out of the 129 plots from farmers with more than one plot, the difference is higher than 30%. This relatively bigger difference, compared to fertiliser and herbicides, might be reasoned through individual plot characteristics, i.e. distance to home or different techniques to control for weeds. Again, the differences between farms in the same village are bigger. To sum it up, on-farm use of fertiliser, herbicides or labour are similar on farm-level, whereas there is a significant heterogeneity between farms, even within a village. Different input choices on neighbouring plots, might depend on different preferences of the farmers. However, since farmers have their plots in different parts around their village, similar on-farm input choices might indicate that unobserved heterogeneity on village level is rather small. This structure in the data seems to be favourable for the analysis at hand.

The relatively high share of inconsistent observations in the HL lottery is not desirable and the source of this behaviour is unclear. As IHLI and MUßHOFF (2013) discuss, it might be a lack of understanding, whereas HARRISON et al. (2005) argues such behaviour is the result of being indifferent between the options. However, as discussed in Section 2.2, by including various HL-measures, i.e. HL-value, HL-consistent and HL-change, we account for this problem.

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, which we consider to be the most important inputs. For fertiliser and herbicides, the high standard deviation in relation to mean values can be explained through the high share of zero-value observations. The labour use per year was estimated by the farmers according to their different tasks on the plot.

Table 2. Socioeconomic, experimental and production data

	Mean	Standard deviation
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
HL-consistent[a)]	3.85	2.95
HL-total	4.39	2.42
HL-change	2.46	2.58
Observations rubber plots	260	
Yield, kg	3,167	3,441
Fertiliser, kg[b)]	78.2	224.8
Herbicides, litre[b)]	5.45	9.79
Labour, hours/year	964	612
Plot size, hectare	2.07	1.84
Plantation age, years	19.30	9.14

Note: a) 137 observations have consistent results for the HL lottery. b) Fertiliser and herbicides have 192 and 138 zero-value observation, respectively.
Source: own presentation including data from DRESCHER et al. (2016), EULER et al. (2016), GATTO et al. (2015)

4 Results

In Section 4.1, we show the estimated influence from production inputs on output variance, i.e. output risk. Thus, we can respond to the first hypothesis. Section 4.2 shows the correlation between the experimentally measured risk attitude and the input use. In combination with the results from Section 4.1, the second hypothesis is answered.

[3] For each of the three HL-measures, the differences between the first and the second lotteries are not significant at the 5% level.

4.1 Estimated Inputs' Influence on Output Variance

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 the amount of input use, which implies heteroskedasticity. Therefore, we apply White's procedure in order to obtain heteroskedastic robust standard errors (WOOLDRIDGE, 2002). The results of this estimation can be seen in Table A1 in the appendix. Five out of the twenty estimated coefficients are significantly different from zero at the 5% level. However, it is evident that neither labour, nor plot size, contribute any significant coefficients to output level. To investigate this, we tested with a likelihood-ratio test for both of these inputs, whether an estimation without either labour or plot size (including the respective interaction effect) nests the estimation shown in Table A1. We found that both of these inputs significantly contribute to the explanatory power of the estimation shown in Table A1. Additionally, an F-test strongly indicates the existence of unobserved, constant effects on village level. However, even though none of the first-order parameters are significant, the adjusted R-square of 0.617 indicates a high degree of explanatory power of the estimated production function. Therefore, we are confident that our data base is sufficient for a well-estimated production function.

To estimate each input's influence on output variance, we apply the translog variance function shown in Equation (3). By including fixed effects, we account for variance effects on village level. Additionally, we introduced three correction dummies: one for fertiliser, one for herbicides and due to the possible interaction of effects between fertiliser and herbicide usage, one for observations with non-zero values of fertiliser and herbicides. This method allows us to estimate unbiased elasticities in the presence of variables including zero-value observations. The correction dummies are not interpreted (BATTESE, 1997). As demanded by the model, all variables are applied in logarithmic values (JUST and POPE, 1978; 1979), including also non-decision variables like plantation age or plot size, as done by other researchers (GARDEBROEK et al., 2010). The estimation results of Equation (3) can be seen in Table 3.

In the translog specification of Table 3 it can be seen that from the 20 variables which are not correction dummies, three are significantly different from zero at the 5% level. This low share of significant coefficients for such regressions can also be found in other studies, e.g., 4 out of 35 in GARDEBROEK et al. (2010). However, the adjusted R-square of 0.623 indicates a high explanatory power of the output variance with the used inputs. An F-test indicates the effects of an unobserved village constant on the output variance. By investigating village level effects we found that approximately 10.8% of the variation between villages

Table 3. Elasticities of input use on output variance, translog specification

	Mean	Standard Error[a)]	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		

Note: significantly different from zero at the *10%, **5% and ***1% levels
Source: own presentation

can be explained with regional variables. Thus, the output variance differs between regions from high to low in the following order: the south-western region of Sarolangun, the north-western Tebo and Bungo regions, the central region of Batang Hari, and the eastern region of Muara Jambi. It can thus be determined that regional differences exist with respect to the output risk in rubber production.

Since each input appear multiple times in the translog specification indicated in Table 3, i.e. directly and through interaction effects, it is not possible to identify the influence of inputs on output risk directly. Thus, for convenience purposes, we estimate the variance function in the Cobb-Douglas specification, i.e. without interaction effects. The results are shown in Table A2 in the appendix. The coefficients of this estimation indicate already the general influence of inputs on output variance: plot size is clearly risk-increasing, whereas fertiliser, with a p-value close to the critical level of 10%, is indicated to be risk-reducing. No significant parameters were found for the other inputs. However, since a likelihood-ratio test notably shows that the Cobb-Douglas specification does not nest the translog specification, further analysis considers only the later named specification.

With respect to the first hypothesis, *"H1: The intensity of used production inputs has an influence on output variance"*, Table 3 shows that three out of 20 combinations of inputs have a significant influence on output risk. Therefore, we cautiously support the first hypothesis, since at least some interaction effects have an influence on output risk.

To determine the inputs' influence on output variance, we apply Equation (4) with the parameters of the translog specification from Table 3. 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 variance. To find such direction, we compare the number of variance-increasing and variance-reducing observations for each input. It is difficult, however, to determine at which proportion of variance-increasing and variance-reducing observations, an input's influence on output variance is distinct. In order to determine the direction of inputs' influence on output variance, we determined that having more than 75% of the observations point in the same direction is sufficient. In the literature for Equation (4), mean values are often used to calculate inputs' marginal influence on output risk (e.g. see ASCHE and TVETERÅS, 1999) or output height (GARDEBROEK et al., 2010). However, since we are interested in the direction exclusively, and not in the size of the effect, we wanted to take a closer look. Therefore, we used a method that calculates the effect for each single observation.

Table 4 shows the influence of each input on output variance per observation. For all 68 non-zero observations of fertiliser usage, the marginal effect is variance-reducing. This finding is already indicated with a p-value of 10.1%, according to the Cobb-Douglas specification of Table A2 in the appendix. Moreover, the marginal effect of herbicide usage is variance-increasing for a clear majority (93%) of the non-zero-value observations. In rubber production, herbicides are used to reduce work effort for weed control, rather than for yield security. Additionally, PANNELL (1991) mentions that even pesticides can be a risk increasing production input. Thus, this result for herbicides seems reasonable. Here, we determine a divergence from the Cobb-Douglas specification of Table A2, where no significant influence is found. This might be due to the missing significant interaction effects of labour and plot size. For plot size, we found a variance-increasing effect for 76% of the observations. Therefore, we carefully consider this production input to be variance-increasing, which is also found in the Cobb-Douglas specification of Table 2A. We have no clear explanation for this effect, but it may be reasoned that bigger plots are more difficult to manage or suffer a higher weed infestation. However, the observations of variance-increasing and variance-reducing marginal effects for labour and plantation age

Table 4. Marginal effects of inputs on output variance

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

Source: own presentation

are almost equal, making the influence on output variance ambiguous. Thus, we leave this input out for further analysis. Since our measure for output risk is output variance, fertiliser is considered as risk-reducing, whereas herbicides and plot size are both risk-increasing production inputs.

4.2 Correlation of Experimentally Measured Risk Attitude on Input Use

To get a rough insight, we first use a left-censored tobit regression to test for a linear relationship between input density, i.e. the amount of input used per hectare, and the three described HL-measures. In a separate regression, we tested with a dummy if farmers with a HL-value above the median have a different input density. Since the plot size is not a decision variable, we leave it out for further analysis. The results are shown in the appendix in Table A3 and indicate no significant differences, except for HL-total for herbicide use. Since this is a pretty rough estimator where F-tests show little explanation power of the regressions, we investigate further.

For the context at hand, what is more important is not the absolute input use, but the over- or underuse of an input. Thus, with x^{Δ} we also test the deviation from the profit maximising input use, rather than the absolute input use. Since the scale in the risk attitude measuring experiment is arbitrary, a linear relationship would be as reasonable as a quadratic one. Consequently, we estimate both of them.

According to Equation (9), 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. Since plot size is not a decision variable, we leave it out for further analysis.

Table 5 shows the influence of the HL risk attitude measures on over- or underuse of fertiliser and herbicides. Here, the right-hand side shows the influence of the HL-measures on input use per observation. The estimated coefficients from Equation (10) regarding fertiliser and herbicides are presented, each with results for HL-consistent, HL-total and HL-change. A previous estimation with only the linear HL-measures (not shown), indicates a negative correlation for HL-total and HL-change with fertiliser at a small significance, whereas for herbicides no significance is found. Due to the low explanatory power of this model in terms of R-squared, we also provided a quadratic model, which has superior explanatory power. A higher HL-measure indicates a farmer having a higher degree of risk aversion. Moreover, the respective marginal effect of these HL-measures on x_{kpv}^{Δ} is calculated (Equation (11)). As with 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-reducing while herbicide was found to be risk-increasing (Table 4).

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 (10))				Marginal effect of the respective HL-measure on over- or underuse of input (Equation (11))			
	Linear (γ_1)		Squared (γ_2)		Positive marginal effect $\frac{\partial q(x_{kpv}^{\Delta})}{\partial HL_i} > 0$		Negative marginal effect $\frac{\partial q(x_{kpv}^{\Delta})}{\partial HL_i} < 0$	
	Mean	p-value	Mean	p-value				
x_{kpv}^{Δ} **Fertiliser**								
HL_i-consistent[b) c)]	-272.2	0.025**	24.940	0.051*	78.0%	32/41[d)]	22.0%	9/41[d)]
HL_i-total[b)]	-154.0	0.115	9.865	0.338	85.3%	58/68[d)]	14.7%	10/68[d)]
HL_i-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_i-consistent[b) c)]	4.510	0.034**	-0.629	0.017**	21.3%	16/75[d)]	78.7%	59/75[d)]
HL_i-total[b)]	2.469	0.142	-0.287	0.144	21.3%	26/122[d)]	78.7%	96/122[d)]
HL_i-change[b)]	3.484	0.021**	-0.516	0.011**	36.9%	45/122[d)]	63.1%	77/122[d)]

Notes: 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 higher 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.
Source: own presentation

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 significantly different from zero at the 5% (or close) level, which strongly indicates a relationship between these HL-measures and fertiliser 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-reducing) fertiliser. Thus, with respect to fertiliser input, we find consistent results for input use and experimentally measured risk-aversion.

For x_{kpv}^{Δ} herbicides, we found a pattern within the significance levels that is similar to the outcome for fertiliser. While the coefficients of HL-total are not significantly different from zero, the coefficients of HL-consistent and HL-change are significant at the 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 usage can be seen for more than 75% of the observations. For HL-change, with a share of 63.1%, the marginal effect is ambiguous. Overall, results slightly indicate that more risk-averse farmers use less (risk increasing) herbicide. This indicates consistent results for herbicide use and experimentally measured risk-attitude.

With respect to the second hypothesis *"H2: More risk-averse farmers use more risk-reducing and less risk-increasing inputs"*, we find that more risk averse farmers use more (risk-reducing) fertiliser and less (risk-increasing) herbicides. Consequently, we support hypothesis two. It seems that participants' field behaviour towards risk and their experimentally measured risk attitude, are consistent with regards to the example of using risk-influencing production inputs. In other words, results suggest a relationship between experimentally measured risk attitude and production decision behaviour for the context of this article.

5 Conclusions

Production output in agriculture can vary considerably, making farming a risky business. Literature indicates that such output variance, i.e. output risk, 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, specifically with respect to output risk and, thus, in better handling of changing circumstances. This is relevant for farmers, as well as for the development of proper policy measures. This research is done for the case of rubber farmers in Jambi province on Sumatra, which is a relevant rubber producing region in Indonesia. The output risk of rubber production 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 intensity of used production inputs has an influence on output variance" and "H2: More risk-averse farmers use more risk-reducing and less risk-increasing inputs", a JP production function was estimated to determine inputs' influence on output variance. Furthermore, a HL lottery was used to experimentally measure farmers' risk attitudes. We find that fertiliser is a variance-reducing input, whereas herbicides and plot size are variance-increasing production inputs. In accordance with our expectations, we found that more risk averse farmers use more (risk-reducing) fertiliser and less (risk-increasing) herbicides. These results suggest a consistent relationship between the use of inputs with respect to inputs' influence on output risk and the experimentally measured risk attitude, which we interpret as external validity of the experimentally measured risk attitude.

In the literature the relationship between field behaviour towards risk and experimentally measured risk attitude is unclear. Some articles show only minor significance or inconsistent correlations between field behaviour and experimentally measured risk attitude, while other articles show consistent correlations. Currently, it is purely speculative as to what might explain the varying findings of different authors. However, recent articles which test the external validity of experimentally measured risk attitude in agriculture, find predictive power in emerging economies like Peru (ENGLE-WARNICK et al., 2007) or Uganda (VARGAS HILL, 2009), whereas in industrialised countries like the USA (BARHAM et al., 2014) or Germany (HELLERSTEIN et al., 2013), little or no predictive power is found. Thus, it is possible that experimental participants in developing countries act more representatively in the experimental task, than participants in developed countries. Conversely, ANDERSON and MELLOR (2009) found predictive power in such experiments in the USA; however, the experiment was related to health decisions and not to agricultural production. It can, therefore, be determined that the topic of external validity is still not certain.

With the present article we contribute to this controversial discussion. This discussion, however, demands further contributions. Applying the method in this article to other crops, an evaluation of a farm as a whole, or to other countries could further strengthen the findings. Moreover, extending the method 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) discusses the difficulties of 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.

Our results are relevant for several reasons. First, we tested the external validity of experimentally measured risk attitude with an incentivised HL lottery by comparing the results with those of a JP production function. This is relevant because output risk, defined by output variance, is a direct risk measure. Moreover, influencing output risk with input choice is something that can be done by a vast majority of farmers. Second, we found significant influence of fertiliser and herbicides usage on output risk for rubber production and that the use of these inputs goes along with farmers' experimentally measured risk attitudes. This knowledge can help with managing such risks, and provides important information for farmers, as well as for policy makers. The massive expansion of oil palm plantations in the research area causes considerable negative externalities (KOH and WILCOVE, 2008; LAUMONIER et al., 2010; WILCOVE and KOH, 2010). Since rubber is the obvious alternative to oil palm in this region, increasing the attractiveness of rubber production by knowing how to handle output risk and especially output variance may lead to a conversion to this crop, which would reduce the aforementioned negative externalities resulting from oil palm.

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Appendix

Table A1. Quadratic production function in levels

	Mean	Standard Error[a)]	p-value
Fertiliser	-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
Fertiliser x fertiliser	0.006	0.002	0.003***
Fertiliser x herbicides	-0.613	0.136	0.000
Fertiliser x labour	-0.003	0.001	0.073
Fertiliser x plot size	0.711	0.561	0.214
Fertiliser 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		

Notes: significantly different from zero at the *10%, **5% and ***1% levels. a) heteroscedasticity robust standard errors
Source: own presentation

Table A2. Elasticities of input use on output variance, Cobb-Douglas specification

	Mean	Standard Error[a)]	p-value
Fertiliser	-0.220	0.134	0.101
Herbicides	0.004	0.121	0.973
Labour	-0.112	0.154	0.470
Plot size	0.450	0.155	0.004***
Plantation age	0.053	0.150	0.724
Dummy fertiliser	*-2.451*	*1.633*	*0.135*
Dummy herbicides	*0.107*	*1.136*	*0.925*
Dummy fertiliser x dummy herbicides	*-0.177*	*0.399*	*0.658*
Constant	6.623	2.668	0.014**
Observations	260		
Adjusted R-square	0.491		

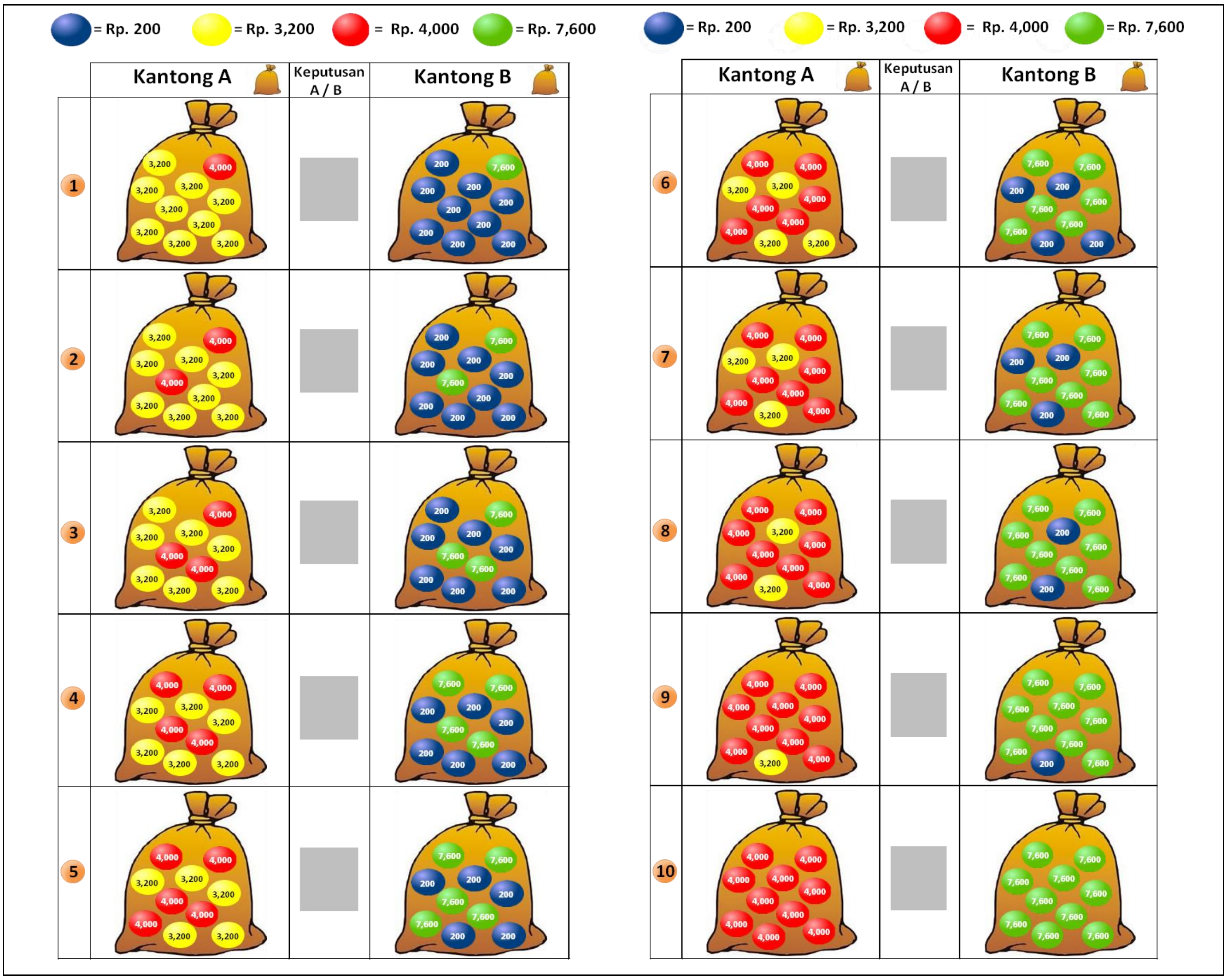
Note: significantly different from zero at the *10%, **5% and ***1% levels.
Source: own presentation

Table A3. Effect of HL-measures on fertiliser and herbicide use per hectare.

	HL_i-consistent		HL_i-total		HL_i-change	
	Mean	p-value	Mean	p-value	Mean	p-value
Fertiliser: Model 1[a)]						
HL-measure	-3.812	0.735	-8.550	0.399	2.685	0.777
Intercept	-127.356	0.029**	-148.282	0.007***	-193.971	0.000***
Fertiliser: Model 2[b)]						
Dummy	-53.426	0.357	-71.144	0.138	-35.055	0.493
Intercept	-119.966	0.007***	-137.327	0.002***	-159.931	0.002***
Herbicides: Model 1[a)]						
HL-measure	-0.282	0.358	-0.438	0.080*	0.022	0.924
Intercept	2.099	0.133	1.259	0.296	-0.661	0.468
Herbicides: Model 2[b)]						
Dummy	-2.525	0.117	-4.038	0.001***	-1.576	0.219
Intercept	2.068	0.007***	2.203	0.002***	0.553	0.002***
N	137		260		260	

Note: significantly different from zero at the *10%, **5% and ***1% levels. a) Model 1 estimates the linear relationship of the respective HL-measure and the input use. b) Model 2 estimates the relationship of the input use and the respective HL-measure according a Dummy accounting for HL-values above the median.
Source: own presentation

Figure A1. HL lottery



Source: authors' illustration following IHLI and MUßHOFF (2013)