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The Impact of Crop Insurance on Indonesian Rice Production

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Abstract

This study builds a theoretical model of the yield-based MPCI crop insurance policy for a risk averse rice farmer in Indonesia and presents the comparative statics analysis of policy variables on yield through the coupling, wealth, and insurance effects. Moreover, Using yield data from 1979 to 2014 for the Tuban Regency, this study applies numerical optimization to the model and simulates the effects of different policies on input use, certainty equivalents, indemnity payment, and premiums. The theoretical analysis shows that no coupling effect exists for change in the coverage level, while a coupling effect exists for change in the subsidy implying that farmers can impact the size of their payments by adjusting inputs and thus yield. For wealth effect, if the price market higher than the average cost of production, the wealth effect is ambiguous. If the price market smaller than the average cost of production, the wealth effect for the coverage levels is ambiguous, while the wealth effect for subsidy levels is negative, indicating a marginal increase in the subsidy reduces input use. For insurance effect, the analysis shows a positive sign for coverage level, revealing that an increase in the coverage level triggers the farmer using more inputs. On the other hand, the insurance effect for subsidy levels generates a negative sign, where higher subsidy cause the farmer to reduce input use. The numerical analysis shows that MPCI crop insurance indicates a moral hazard. At coverage levels $\leq 30\%$, the farmer does not expect to receive any indemnity payment. However, for coverage levels at or above 40%, the farmer expects indemnity payments, which triggers a reduction in input use as the farmer tries to maximize both insurance payments and market revenue simultaneously. For certainty equivalent, farmers prefer the highest coverage level. For expected indemnity and insurance payment, farmers receive the highest payment for the largest high coverage level and subsidy. Hence, the result indicates that MPCI insurance with high coverage levels and low premium subsidies is suggested to Indonesian government since such policy results improving the farmers' wellbeing while mitigating moral hazard facing the insurance provider.

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Dedication

This thesis is dedicated to my beloved parents, M Yunus Yahya and Zubaidah Hasballah, who have making me more than I am. It is also dedicated to all the people who have offered their time, support and commitment.

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Chapter 1. Introduction

1.1 Background Information

Rice is one of the world's most important staple food crops as nearly 50 percent of the world population consumes this commodity (Mohanty, 2013). Rice comprises about 10 percent of the world's agricultural land and accounts for around 20 percent of total global grain production (Thorburn, 2015). In Indonesia, rice is particularly important both as a subsistence crop and for the livelihood for rural farmers.[1] As the main staple food, rice provides nearly half of the caloric intake of an average Indonesian (Pasaribu, 2010). Rice is the foremost commodity grown in Indonesia with rice area in 2015/16 estimated at 12.2 million hectares, attributing to 30 percent of total planted area in the country (Shean, 2012, 2015).

In Indonesia, rice production is highly concentrated on the islands of Java and sumatera, and 60 percent of total production comes from Java alone (Shean, 2012). Figure 1.1 shows the top five Indonesian rice producing provinces: (1) South sumatera, (2) West Java, (3) Central Java, (4) East Java, (5) South Sulawesi (Indonesia-Invesments, 2015). The 2013 national census data published by Badan Pusat Statistic (Central Bureau of Statistic) indicates that among the 26.14 million of total agricultural households in Indonesia, 70 percent are rice farmer households. These households own very small farms with an average size of less than 1 hectare (the majority of farmers cultivate 0.1 - 0.5 hectares) and have attained low education levels (only 1.94 percent earn a Bachelors degree) (Shean, 2012; BPS, 2014).

According to FAO (2016), Indonesia is the third largest global rice producer after China (first) and India (second). However, Indonesia is still a net rice importer because consumption continues to outpace supply as the Indonesian population grows. Indonesia has imported rice for multiple decades. Figure 1.2 shows Indonesia's rice production, consumption, and imports from 1960 to 2015. President Suharto implemented a policy of heavy subsidy for

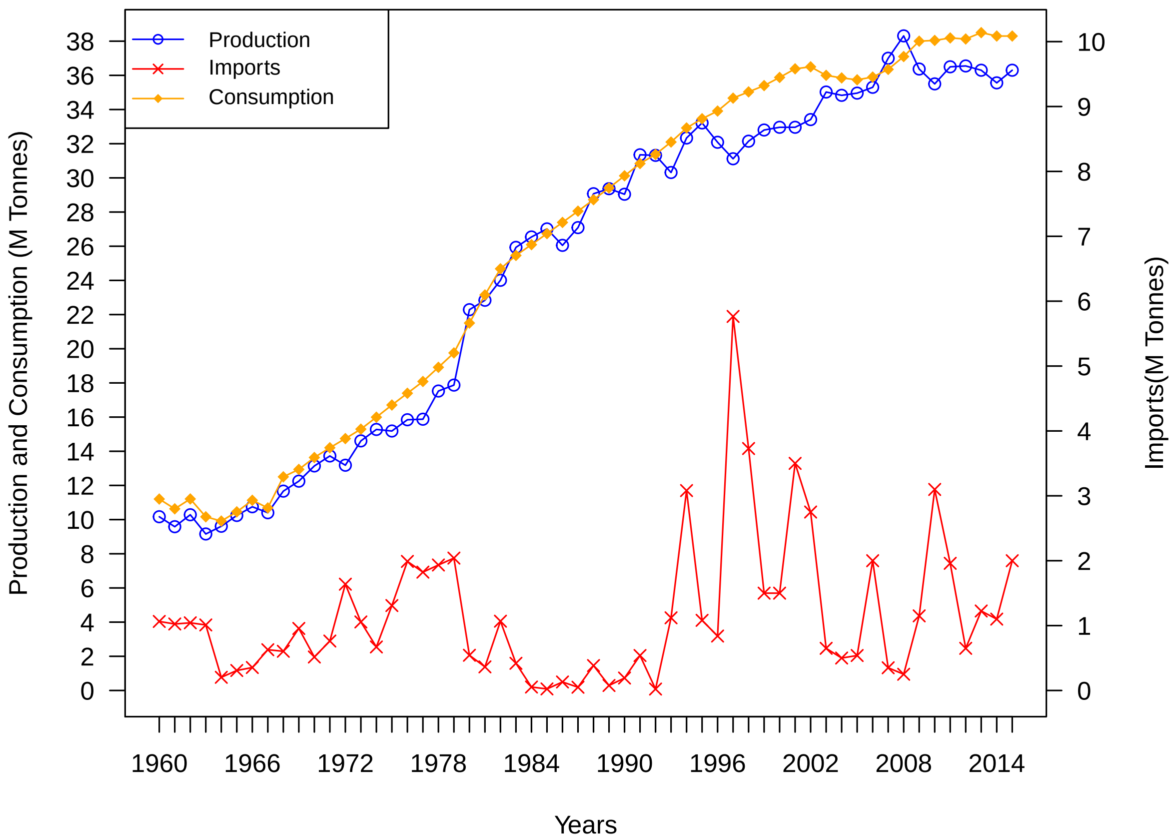
[1]This holds true for many Asian countries where rice accounts for 90% of global rice consumption and occupies about one third of total agricultural land (Thorburn, 2015; GRiSP, 2013).

Figure 1.1: Indonesia: Rice Central Production

Source: (Indonesia-Invesments, 2015)

rice production in 1970sand 1980s with the objective of achieving self-sufficiency; this was first achieved in 1984 when imports reached zero. The government implemented fertilizer subsidies and constructed irrigation infrastructure, which were key for newly developed high-yielding rice varieties (Trewin and Erwidodo, 1993). However, the high costs (high budgetary expenditure, economic inefficiency, welfare costs, and environmental damage) associated with such policies resulted in only temporary self-sufficiency (Trewin and Erwidodo, 1993). Imports subsequently increased as production could not keep pace with the population growth. From the mid-1990s onwards, Indonesia has been a net importer of rice although the magnitude of its imports varies year to year depending on domestic production. In fact, from 1998 to 2001, four years following the Asian financial crisis of 1997–1998, Indonesia became the largest rice importer in the world at 18 percent of the world's total imports (Warr, 2005). Figure 1.2 reveals that historical growth rates of rice production appear to be slowing compared to the 1970s and the 1980s. The average growth of rice production is about 600 thousand tones per year between the year 1960 and 1987, but has since slowed to nearly 300 thousand tones per year between 1988 and 2014. This figure also shows that since 1983 rice production has greatly fluctuated. Pests and diseases outbreaks, natural disasters such as floods and droughts, and global change of climate are some of the mainsprings that causes variability of rice pro-

Figure 1.2: Indonesia: Rice Mill Production, Consumption, and Import (Million Tonnes)



Source: Author's calculation using data from IndexMundi

duction (Pasaribu, 2010). Therefore, many poor Indonesian rice farmers face substantial risks, making their income and main food source highly vulnerable to variables outside of their control.

The national census reported that 39.96 percent of rice farming households experienced crop loss due to pests and diseases in 2013 (BPS, 2014). Pests and diseases caused a national production loss of about 327 thousand tons in 2008 (Pasaribu, 2010). Moreover, because of brown plant hopper outbreaks, rice crop production in 1998 and 2011 declined by 12% compared to the preceding years (Sudaryanto, 2014). Rice farming in Indonesia is also risky due to natural disasters (Sayaka and Pasaribu, 2014). Given the country's location on the Pacific Ring of Fire, almost all areas in Indonesia are frequently plagued by earthquakes, tsunamis, floods, and droughts, resulting in destructive effects on the land area and ruining food crop harvests. Table 1.1 provides the number of natural disasters that have occurred since 1970 and their impacts on all crops. The table indicates that during the period 1970-2011, a total of 3,446,708 ha of crops were damaged as a result of 7,576 hazard events. Sudaryanto (2014) reports that between 2007 and 2013, 8% of an annual average of 13.12 million hectares of rice crop in Indonesia are vulnerable to natural disasters. The 2005 earthquakes that happened in Nias Island (North sumatera) devastated the irrigation infrastructure, caused drought in the agricultural areas, and reduced the rice production rate due to a disruption in production (Lassa, 2012). Many other places in Indonesia encounter similar losses after disasters occur. Natural disasters that impact agricultural production will adversely affect the livelihood of many farmers because these agricultural households, where the majority are small scale subsistence farmers living in rural areas, are affected significantly by such losses which, not only impacts on their ability to feed themselves, but also to earn income.

Climate change is another risk that Indonesian rice farmers face. Climate change will likely lead to a sea level rise and changing precipitation patterns which will lead to more uncertainty in Indonesian rice agriculture. Indonesia is an archipelagic country where many agricultural activities are located along the coast and increasing sea level may account for a loss of agricultural land due to inundation and increased soil salinity, influencing crop growth and yield (Forster et al., 2011). Also, changing precipitation patterns will increase uncertainty associated with water availability and the ability to produce water intensive agricultural commodities such as rice (Forster et al., 2011). In other words, climate change causes agricultural activities to become more unpredictable due to the irregularity of harvest and planting seasons. Climate change also increases the frequency of El Nino events that frequently hit Indonesia (Case et al., 2007). El Nino events will exacerbate dry and wet seasonal trends by triggering more extreme droughts in the dry season and more extreme floods in the wet season. Nearly 426,000 hectares of rice crop area were affected by the El Nino droughts in 1997 (Measey, 2010). The national census survey in 2013 revealed that about 48 percent of households that

Table 1.1: The Number of Natural Disasters and General Crop Damage Assessments

Type of hazards	**Σ events**	**Σ of crop damages (ha)**	**Average Crop damage (ha/event)**
Floods 1970-2011	3,980	1,187,349	298
Drought 2003-2011	1,411	1,667,766	1,182
Earthquake-Tsunamis 1970-2010	268	60,673	227
Landslides 1999-2011	1,596	52,273	33
Landslides + Floods 1970-2011	305	287,046	941
Plague 1990-2009	17	191,601	11,271
Total	**7,576**	**3,446,708**	**455**

Source: (Lassa, 2012)

grow wetland paddy experienced a 25 percent decline in production or productivity due to climate change **(BPS, 2014)**.

The risks caused by pest and disease outbreaks, natural disasters, and the effects of climate change are particularly difficult for the 41.7% of rural rice farming households that the 2004 National Socio-Economic survey (Susenas) classifies as poor (McCulloch, 2008). Because more than 85 percent of farm households are self-funded (the remaining 15% of the households have access to farm credit), production risks may contribute to the decline in the total rice farming area because, when substantial crop loss occurs, farm households may sell their assets such as land for income (Bappenas, 2014). In fact, the 2013 national census data reported that 19.02 percent of farm households would sell their land in order to deal with the funding constraints (BPS, 2014). Furthermore, risk-averse individuals may change investments decisions from agricultural investments into non-agricultural investment because of high risks associated with agricultural activities, especially in the suburban areas where much of agricultural land turns into new manufactury infrastructures and urban homes. During the period from June 1998 to June 2003, nearly 12,600 hectares of total rice land were converted into non-agricultural land (Bappenas, 2014). In addition, the average rice area expansion rate went from 138,000 hectares a year between 1960-1998 to only 9,000 hectares a year between 1999-2010 (Shean, 2012). Therefore, a risk transfer instrument is needed to assist farmers mitigate the risky rice production activity.

Agricultural insurance is one of the financial tools that can assist agricultural producers in mitigating risks attributed to adverse natural events (Mahul and Stutley, 2010). Crop insurance has been widely used in high-income countries to reduce farm income instability. In recent years, governments in many developing countries have started studying the benefits of agricultural insurance, and some have even implemented pilot insurance programs. In Indonesia, because rice is a crucial commodity and is a major source of livelihood for many small scale subsistence farmers, the Ministry of Agriculture developed the pilot Asuransi Usaha Tani Padi (AUTP) insurance program for the planting season of 2012-2013. This program was designed to promote agricultural development, food security, and mitigate risk against crop yield loss due to pests and diseases outbreak, earthquakes, tsunamis, floods, and droughts (Pasaribu and Sudijanto, 2013). Before this pilot project was implemented, several studies were conducted to explore the effect of farmers' perceptions on agricultural insurance as the platform to conduct the pilot project.

1.1.1 Background on Agricultural Insurance in Indonesia

The Indonesian Center for Agricultural Socio-Economic and Policy Studies (ICASEPS), a division under the Ministry of Agriculture, conducted the first survey study on rice farm insurance in 2008 to evaluate farmers' perceptions on agricultural insurance (Pasaribu, 2010; Sayaka and Pasaribu, 2014). The survey was conducted in collaboration with the Food and Agriculture Organization (FAO) and administered in two key rice producing regions: Simalungun Regency of North sumatera Province and Tabanan Regency of Bali Province.[2] The following year ICASEPS continued to administer the survey in the same provinces and regencies, but the funding was only from the Ministry of Agriculture. In Simalungun Regency, the survey was administered to farmers in two villages (with a total planted area of 510 ha or 0.6% of the total rice area in the regency), whereas in Tabanan Regency the survey was conducted in only one village (with a total planted area of only 300 ha or 1% of the total rice area in

[2] Rice area in Bali is account for 23% of agricultural area in the province (BPS-Statistic of Bali Province, 2014).

the regency). In 2010, the survey was expanded to Deli Serdang Regency in North Sumatera Province and to Jembaran Regency in Bali Province. Surveys were conducted only for farmers (around 30 to 40 farmers or 1% of the farmers) who encountered harvest failure due to pest and disease attacks (e.g. brown plast hopper, rats, and blast), flood, and drought. Based on the survey, the calculation of the sum insure (the maximum indemnity the farmer could receive) was based on the size of planted area, harvested area, yield, and cost of production of paddy rice at the village level within the subregencys. However, an insurance claim that was equal to the production value was most preferable by the farmers. The survey revealed that the farmers in both provinces responded positively toward the agricultural insurance and they expected the agricultural pilot project to be implemented in 2012.

The first pilot Asuransi Usaha Tani Padi (AUTP) or rice insurance program was implemented in the planting season of 2012-2013. The insurance covered the risks caused by pests, diseases, flood, and drought. AUTP was an indemnity based crop insurance given to a group of farmers (kelompok tani/POKTAN) in East Java Province and South sumatra Province (Kawanishi and Mimura, 2015). In indemnity based crop insurance, the insurance claim was determined by measuring loss or damage in the field soon after the damage occurs and the damage measured in the field was applied to the agreed sum insured for the crop (Bryla-Tressler et al., 2011).

Initially, the pilot project was planned to be implemented in three provinces: South Sumatra, West Java, and East Java. However, due to some technical reasons,[3] the pilot project was conducted only in South Sumatra and East Java (Sayaka and Pasaribu, 2014). In East Java Province, the pilot rice crop insurance was conducted for 470.87 ha (0.3 % of the total rice area) occupied by 25 groups of farmers located in Tuban and Gresik regencies. Whereas, the pilot program in South Sumatera Province was implemented for 152.25 ha (0.13% of the total rice area) owned by 17 groups of farmers in East OKU regency (Sudaryanto, 2014). For the pilot project, the payment to the farmer or sum insured was determined based on the aver-

[3]Lack of field coordination in the province of West Java (Pasaribu and Sudijanto, 2013).

age cost of production per hectare in the two provinces, which was 500 USD per ha. Farmers could make an insurance claim only if total crop damage was greater than or equal to 75% of the total planted area, and the payment was equal to the sum insured times the number of damaged acres (Pasaribu, 2013).[4] The total premium cost was 15 USD per ha, of which the government subsidized 80% (or 12 USD per ha) and the farmers were only required to pay 20% (or USD 3 per hectare).

As reported by Pasaribu and Sudijanto (2013), the farmers in Tuban and East OKU regencies experienced heavy flooding, and over 75% of the total planted area, approximately 80 ha of the total area in Tuban regency and 7.28 ha of the total area in East OKU regency, were affected by the flood. Therefore, payment was made to cover the damage. Since the total area claimed was 87.28 ha (Tuban and East OKU regency), the total indemnity payment in the both regency received was around 43,640 USD. Pasaribu and Sudijanto (2013) showed that the pilot project worked successfully and they recommended that a similar pilot project should be further expanded.

Correspondence with Pasaribu (2015) explained that in 2015, the government has allocated approximately 140 Million USD to support this agricultural protection instrument. While the indemnity based crop insurance provides some protection to rice farmers against disasters, yield-based Multi-Peril Crop Insurance (MPCI) crop insurance, as is implemented in many developing countries around the world, is a more feasible and accurate method to insure rural rice farmers. Therefore, the Ministry of Agriculture is considering MPCI crop insurance programs in Tuban and Gresik, where sufficient data exists. Therefore, studying the impact of MCPI insurance in these two key growing regions will be valuable to policy makers in the Ministry of Agriculture.

1.2 Objective

The present study aims to: 1) develop a model of a risk-averse Indonesian rice farmer with access to yield-based MPCI crop insurance, 2) derive comparative statics for changes in

[4] Insurance claims were paid within 14 working days.

premium subsidies and coverage levels on the coupling, wealth, and insurance effects, 3) calibrate the model to a representative rice farmer in Tuban regency in Indonesia, 4) apply numerical optimization to the model and simulate the effects of different coverage and subsidy levels on input use, certainty equivalents, indemnity payments, and premiums.

1.3 Organization

The organization of this thesis is as follows. The second chapter reviews the literature on crop insurance in Indonesia and crop insurance in developing countries. The third chapter develops a theoretical model detailing the mathematical formulation of crop insurance and provides theoretical analysis of wealth, insurance, and coupling effects. The fourth chapter presents numerical analysis that consist of three sections: (1) data, yield distribution, and calibration, (2) the simulations and results, and (3) conclusion and recommendation. The final chapter provides the summary, the main conclusions, and the potential extension of the thesis.

Chapter 2. Literature Review

Although voluminous literature on crop insurance for developed countries exists, economic analysis of crop insurance in developing countries has received comparatively little attention. Despite relatively minimal academic attention, many developing countries have established crop insurance programs to mitigate risks to farmers. This chapter critically reviews previous academic studies on crop insurance in Indonesia as well as other developing countries. Then this chapter discusses the difference between past studies and the contributions of this study to the literature.

2.1 Crop Insurance in Indonesia

Crop insurance for rice production was first introduced in Indonesia in 2012 on a pilot basis, and as such, very few studies have considered the impact of this policy on farmers. Before the implementation of the pilot project two studies examined the importance of crop insurance to mitigate risk associated with agricultural production. After the pilot project was actualized, only one study has analyzed whether it would be feasible to implement different types of crop insurance policies that were not part of the pilot project.

Before the implementation of the pilot project, Kansal and Suwarno (2010) analyzed five concepts of integrated risk management to address agricultural risks[1] in the Way Jepara irrigation area in the province of Lampung on Sumatra island. The integrated risk management concepts include (1) risk identification, (2) risk assessment, (3) decision making under risk and uncertainty, (4) implementation of integrated risk management, and (5) and monitoring of integrated risk management. The risk identification process was studied by utilizing several tools and methods such as official documents, environmental scans, on-site inspections, interviews, and statistical analysis. Most of the official documents in 2008 were analyzed in this study.

[1] The authors identified several areas of risk (earthquake, drought, flood, deforestation, erosion, failure of irrigation systems, soil degradation, pests and disease, political instability, and inappropriate laws and regulation) faced by Indonesian farmers.

The process of risk assessment was examined by analyzing the probability and the magnitude of losses caused by natural calamities (earthquake, drought, flood), pest and disease outbreak, and political and economic situation. Decision making under risk and uncertainty analysis focused on actions if a given risk is realized. For example, the authors recommend crop insurance as a risk transfer action for earthquake, drought, flood, failure of irrigation systems, soil degradation, and pests and disease. Implementation of integrated risk management examined several practices and methods to be implemented in the Way Jepara irrigation area. Among many practices and methods crop insurance is one of the methods suggested to be implemented, especially multi peril crop insurance (MPCI), because such insurance can cover many perils.[2] The author also emphasized monitoring integrated risk management to ensure that all of the methods and practices are administered as expected. The results showed that the widespread damage from the identified risks has a massive adverse impact on the irrigation and cultivated area. This impact ultimately reduced yield and farmers' incomes which exacerbates both poverty and hunger in the long term. Based on these results, a risk transfer instrument such as crop insurance is proposed as one of the key methods to minimize the impact of the risks burdened by farmers.

Pasaribu (2010) presented a formal analysis to formulate a pilot program before crop insurance was made available to the Indonesian rice sector. A survey of farmers and other stakeholders regarding the possibility of implementing rice farm insurance was discussed in the paper. Pasaribu (2010) designed a survey of rice insurance for farmers in two villages (Panombeian Panei in the Simalungun regency in North Sumatra province and One Subak in the Riang Gede regency in Bali province) in order to obtain farmers' perspectives on rice farm insurance. The survey demonstrated that rice farmers and local governments responded enthusiastically toward the plan of implementing insurance in their areas. The two regencies committed to coopera-

[2]In addition to crop insurance, the author's also recommend catchment area management, sediment and flood control, irrigation management and practices, fertilizer application, management of pests, weed, and disease, strengthening of legal system, and improvement of laws, regulation, and policies.

tively implementing the crop insurance program by constructing an agricultural insurance task force. While several farmers also agreed to forfeit government premium assistance, a compromise was suggested where the farmers and local government would each pay half of the premium cost. The suggested premium cost was 3.5% of the sum insured typically measure as the cost of production which varies by region. Pasaribu (2010) found that the creation of a rice farm insurance policy should be authorized by the National Rice Insurance Commission (NRIC) formed by The Ministry of Agriculture. This commission consists of several agencies such as the Ministry of Finance, the National Development Planning Agency (Bappenas), and the Ministry of Home Affairs. The NRIC was in charge of constructing that insurance policy package and determining the maximum sum insured, premium rates, and premium subsidy of the insurance. The Ministry of Agriculture then had to approve the final policy package developed by NRIC.

After the realization of the pilot project, Kawanishi and Mimura (2015) analyzed risk to rice farmers in the Tuban and Gresik Regencies in East Java Province to develop a broader risk management portfolio to make the pilot successful and explore the possibility of implementing a weather index insurance for those pilot sites. To provide insight into additional risk management tools, Kawasaki and Mimura analyzed risk prevention by testing whether rice harvest failures during the rainy season for rice farmers located in the Bengawan Solo river basin would be more severe than for farmers located outside the river basin. The Bengawan Solo river basin is the largest basin on Java island in which both regencies, Tuban and Gresik, are located. Heavy floods and landslides frequently occur in this river basin during the rainy season which could adversely affect the magnitude of rice harvest failures in this area. The author employed an independent sample t-test to test if rice harvest failures were statistically different in the Bengawan Solo river basin than in the surrounding areas. The authors used location as the independent variable and the adjusted values of monthly rice harvest failure area as the dependent variable. The independent variable was divided into two location groups: regencies located in the Bengawan Solo river basin and all other regencies in East Java. The adjusted value in the dependent variable is the result of dividing the monthly rice harvest failure area with the total rice area for each of the regencies. The analysis showed that rice harvest failure during the rainy season in the regencies around the Bengawan Solo river basin was significantly larger compared to those in the remaining regencies in the province. This result indicated that farmers in the river basin will receive more indemnity payments when indemnity-based crop insurance is implemented because payments are based on crop losses. Kawasaki and Mimura found that, due to the degradation of Wonogiri reservoir, which was mainly designed for flood control in this basin, floods occur more frequently during the rainy season and can have a tremendous effect on rice production. Hence, risk prevention management in the reservoir, such as rejuvenating the dead storage and upgrading the capacity of the spillway, is suggested to reduce flood risk in this basin so that crop insurance can be implemented.

Next, Kawasaki and Mimura generated scatter plots of monthly rainfall data and rice harvest failure data for the pilot sites from 2000 to 2010 to examine the correlation between the weather parameter and crop harvest failure. The scatter plots are studied to consider the possibility of implementing weather index insurance in the pilot locations. The scatter plots revealed that some tremendous losses occurred without regard to locally observed rainfall, indicating the issue of risk basis (i.e., weather index fails to predict the losses of the insured).[3] Thus, the result indicates that implementing a weather index insurance, where the determination of risk cover based on locally recorded rainfall, is not applicable in the pilot project locations. In this context, weather index insurance cannot be based on locally recorded rainfall and other index metrics would need to be developed.

Kawasaki and Mimura further investigated the potential of basis risk related to weather index insurance by comparing the correlation coefficients of monthly rice harvest failure with the correlation coefficients of monthly rainfall in 29 regencies in the East Java province. The outcome showed that correlation coefficients of monthly rice harvest failures between regen-

[3]The authors emphasized that a huge loss happened in January 2008 was the result of a heavy rain in the upper part of the river, causing severe flood downstream in the basin area.

cies are lower than those of monthly rainfall, indicating that rice harvest failure is more area-dependent than rainfall-dependent in East Java. Therefore, the result further highlights the potential problem of basis risk related to weather index insurance.

Based on this analysis, this thesis provides an in depth analysis of multi-peril crop insurance for Indonesia, which avoids the basis risk of weather index insurance.

2.2 Crop Insurance in Developing Countries

In recent years, crop insurance in developing countries has followed actuarial methods with the objective of mitigating risk to farmers for crop loss due to adverse weather, pests, and disease. As a result, farmers are better able to fulfill essential needs, including food for the family. Several crop insurance studies in developing countries exist in literature;[4] however, this subsection focuses only on papers that study crop insurance in developing Asian countries.

2.2.1 Weather Index Crop Insurance

Research has been conducted to explore the potential for using weather index insurance to provide risk transfer management for poor rural farmers. Giné et al. (2007) provides empirical analysis of rainfall insurance in southern India. The analysis of the study focused on 2006 calender year of insurance contracts. Their study is divided into three distinct sections. In the first section the authors studied the probability distribution of indemnity payments using historical rainfall data from 14 different meteorological department stations in India. This study estimates the hypothetical indemnity payment for each weather station by applying the insurance contract in each station to historical rainfall data. The insurance policy is administered to cover rainfall that occurs in the monsoon season (June to September). The policy contract is differentiated in three stages of monsoon rainfall, i.e., monsoon rainfall during sowing stage, monsoon rainfall during flowering stage, and monsoon rainfall during harvesting stage. The insurance payments in the stage of sowing and flowering are associated with low

[4]See, for example, crop insurance analysis in Burkina Faso (Sakurai and Reardon, 1997), in Hungaria (Spórri et al., 2012), in Kenya (Janzen and Carter, 2013), in Romania (Dragos and Mare, 2014), in Serbia (Birovljev et al., 2015).

rainfall. An indemnity of 10 rupees per each millimeter is paid if the rainfall falls between the upper threshold (70 mm) and the lower threshold (10 mm). The higher indemnity of Rs 1000 (Flat payment) is paid if the rainfall drops below the lower threshold, and zero payment will occur if the rainfall exceeds the upper threshold. However, in the third stage an indemnity is paid if the rainfall goes above the upper threshold of 70 mm. The result of estimated payments in all stages shows that the insurance is not actuarially fair since the average premium is higher than the average estimated indemnity payment. The distribution of indemnity payment reveals that the probability of getting zero payment is 11 percent, the probability of getting indemnity payment double to the average premium is 5 percent, and the probability of getting an indemnity payment of Rs 1000 is 1 percent.

In the second section, they examined whether insurance payouts are correlated through time and correlated across different policy contracts. The averaged standard deviation of 11 contracts for each weather station was calculated and was compared with the standard deviation of the mean indemnity payment averaged across the 11 contracts. This calculation was conducted in order to examine the degree of cross-sectional dependence in the payment. The calculation demonstrated that the standard deviation of the mean indemnity payment is 46 percent smaller than the averaged standard deviation of the contracts, indicating there was a correlation of payment in the cross-section. Moreover, Giné et al. (2007) estimated two autoregressive models in order to check the time-series correlation in the indemnity payment. Stage insurance payment is the dependent variable for both models. The independent variable in the first model is lagged stage payment. While in the second model, two additional variables such as a dummy variable of lagged payment (1 if the lagged payment is greater than 0) and cumulative rainfall in the previous stage, were included as the independent variables. The regressions of both models showed that the degree of persistence in indemnity payment is statistically insignificant. Moreover, both of the additional lagged variables in the second model were not significantly correlated with the insurance payments, indicating that the issue of stale pricing (farmers could take advantage if the insurance providers is late on updating the price before the pricing based on rainfall shocks) was unlikely to happen in the insurance practice.

In the third section, the authors evaluate the correlation between insurance indemnity with several macroeconomic variables such as GDP per capita, the inflation rate, and the change in the Indian treasury yield. The result of the regression showed that none of the macroeconomics variables besides Indian GDP per capita were significantly correlated to the insurance payment. The Indian GDP per capita and the insurance payment develop negative correlation. The economic interpretation of this relationship is that a 1 percent point drop in GDP growth would increase the expected insurance payment around 15 percent.

The following reviews focus on crop insurance studies in Bangladesh. Hossain (2013) analyzed several issues in implementing weather index insurance in Bangladesh.[5] The study found that heterogeneity of farm land and local risk variations, heterogeneity of climatic conditions, limited insurance capacity, and state and external support are the major challenges in actualizing weather index insurance. Heterogeneity of farm land and local risk variations would lead to an inaccurate calculation of indemnity payments and premiums. Heterogeneity of climatic conditions in Bangladesh required a multi-peril weather index insurance to work because a single-peril weather insurance is incompatible to cover crop losses caused by numerous climatic factors. Limited insurance capacity restrained the development of weather index insurance due to the inadequacy of infrastructure and the unavailability of appropriate expertise. The author also argued that lack of state and external support would prevent weather index insurance from working effectively as a risk transfer instrument because the implantation of such insurance would need a government support such as subsidy. As a solution, the author suggested several ways to address the challenges in implementing weather index insurance in Bangladesh: (1) proper preparation for index measurement and premium determination, (2) flexible product design using fewer number of perils and multi-peril options and different risk layering, (3) wider stakeholder involvement, (4) reinsurance facilities from a national and inter-

[5]The author also analyzed the general problem in implementing weather index insurance in a developing country.

national level with technical support and wider area of coverage may increase viability, and (5) proper feasibility studies and further research.

2.2.2 Area-Based Crop Insurance

Area based-crop insurance is another alternative insurance program that is developed to mitigate agricultural risk. Clarke et al. (2015) designed an insurance demand-elicitation exercise for farmers in rural Bangladesh in order to find farmers' interest in insurance products. For the demand-elicitation experiment, farmers were presented with a chart that consisted of three sections in which three categories of insurance were offered: agricultural insurance for the Aman (summer monsoon) season, agricultural insurance for the Boro (winter dry) season, and other types of insurance that offer coverage for the full year (life insurance). Next, each farmer was given 30 stickers that could be used to purchase their preferred type of insurance. However, if the farmers were not interested in buying any insurance they could save their money in their savings account, where each sticker would represent 20 Taka. Moreover, farmers could also choose to save their money in a group savings account that was offered in selected rounds. A group savings account would benefit farmers by lending some money back to the farmers with a low interest loan. The group saving account were worth 5 stickers (100 Taka) if the farmers agreed to opt for the savings account.

The result of the demand-elicitation exercise showed that most of the stickers (around 90 percent) were contributed to the insurances (life insurance and agricultural insurance), whereas only 10 percent were contributed to individual savings. The results parallel with the economic theory stating that farmers will be more interested in buying insurance products that provide coverage for the risks they normally face. However, the farmers' focus varied on the different types of insurance (not only agricultural insurance but also life and disability insurance) since they are exposed to a plethora of risks. The result also established that farmers divided their endowment between life and disability insurance and agricultural insurance. The author realized that the result obtained from the demand-elicitation exercise was considered inaccurate in conveying the demand of insurances because during the exercise, the farmers' choices were framed around risk management that made having any insurance more important compared to other alternatives. Therefore, using the household data affected by each shock collected from Borga Chashi Unnayan Project (BCUP), Clarke et al. (2015) ran a regression to assess whether the demand for each insurance product attributed to the prevalence of the risks faced. The author also ran a regression to see whether the farmers' concern about risk was reported in the Customized Insurance in Bangladesh (CIB) survey. Both of the results were compared and they found that farmers' demand for area yield and drought insurance varies with the prevalence of the risk that the insurance covers (prevalence risk is more sensitive compared to importance risk).

Clarke et al. (2015) also ran a regression of demand for area-yield insurance on price in order to assess the relationship between those two variables (demand and price). The result showed that the demand and price for area-yield insurance established a negative interaction, where the demand of area-yield insurance decreases if the price is randomly increased. Additionally, Clark ran a regression to find how group savings offered in selected rounds would affect the demand for other insurances (life insurances and agricultural insurances). The regression concluded that group savings did not significantly affect a farmer's decision about buying agricultural insurances, but it did significantly affect the demand of life insurances.

Another study focused on area-based yield insurance and multi-peril crop insurance. Using data from wheat farmers in two counties in China, Zhang et al. (2011) established an empirical model for area-based yield insurance (AYI) and multi-peril crop insurance (MPCI). The authors then compared risk reduction percentage and risk reduction percentage per premium of both types of insurances to explore the insurance effectiveness. Using the Kernel-smoothing approach to generate a yield model distribution of both counties, the authors found that MPCI had higher average risk reduction effectiveness compared to AYI; while for the average risk reduction per premium, MPCI and AYI presented consistent values. However, in terms of premiums, MPCI generated greater payment than AYI. This is relevant to the theory that MPCI has the most expensive administration costs and is considered susceptible to moral hazard and adverse selection problems. Although the result of the calculation showed that MPCI has higher effectiveness compared to AYI, the authors suggested that AYI is more applicable in China since the farmers owned very small farms (average size between 3-10 Mu). The transaction costs of MPCI would be very high for insurers and adjusters to identify every small farm's loss claim. The moral hazard and adverse selection problems would also be very serious in China. Nevertheless, the authors noted it is important to ensure the homogeneity of a given area first before using AYI. The result of this study indicated that AYI is more powerful than MPCI in Xingtai County in China, but it has worse performance in Zaoqiang County.

2.3 Contribution to Literature

Since the implementation of the pilot project of AUTP rice farm insurance, few studies have been focused on the feasibility of implementing alternative crop insurance in Indonesia. Kawanishi and Mimura (2015) generated scatter plots of monthly rainfall data and rice harvest failure data to examine the feasibility of implementing weather index insurance in Indonesia. Several studies can be found that closely relate to Indonesian crop insurance by studying the performance of crop insurance in similar developing countries. Giné et al. (2007) estimated hypothetical indemnity payment for weather index insurance in India and built a regression model to find a correlation between the crop insurance and economic growth variables. Zhang et al. (2011) established an empirical model for area-based yield insurance (AYI) and multi-peril crop insurance (MPCI) and compared the effectiveness of both insurances. The authors compared the premium payment, the average risk reduction, and the average risk reduction per premium between area-based yield insurance (AYI) and multi-peril crop insurance (MPCI).

Unlike in any previous study, this thesis develops a model of a risk-averse Indonesian rice farmer with access to yield-based MPCI crop insurance and examines the effect of MPCI policy, such as different coverage and subsidy levels on input use, certainty equivalents, indemnity payment, and premiums. The current study is a pioneering work for MPCI product insurance as there has been no previous study in Indonesia discussing these subjects.

Chapter 3. Theoretical Model and Analysis

This chapter provides the theoretical model of the yield-based MPCI crop insurance policy for a risk averse rice farmer in Indonesia and presents the comparative static analyses of the effect of policy variables on yield through the coupling, wealth, and insurance effects. The theoretical model of the yield-based MPCI crop insurance policy in Indonesia is discussed first, then the analysis of wealth, insurance, and coupling effects is presented.

3.1 Model for Yield-Based MPCI Crop Insurance Policy in Indonesia

Multiple-peril crop insurance (MPCI) allows a farmer to insure again yield losses based on a specified percentage (typically between 50% and 70%) of their historical average yield (Bryla-Tressler et al., 2011). The model represents a wetland risk averse rice farmer in Indonesia that has access to a yield-based MPCI crop insurance policy. The farmer follows a Cobb-Douglas production function that is given by

$$\tilde{y} = z l^{\alpha_l} x^{\alpha_x} + \tilde{\varepsilon} \tag{3.1}$$

where $\tilde{y}$ is the random actual yield per hectare, z is productivity parameter, l is input used for labor, x is the composite inputs that include intermediate inputs (pesticide and fertilizer) and capital, α_is are share parameters, and $\tilde{\varepsilon}$ is a random variable (centered on zero) portraying yield variation. The farmer's market revenue (market price p times random yield) and total cost (wage rate w times labor plus and composite input price r times composite input) per hectare are

$$\begin{aligned} TR(\tilde{\varepsilon}) &= p\tilde{y}, \\ TC &= wl + rx. \end{aligned}$$

Farmers can also enroll in MPCI where they receive an indemnity payment in low production years and pay a premium. The MPCI indemnity payment per hectare is

$$MPCIi(\tilde{\varepsilon}) = p^f \max\left[0, \eta y^h - \tilde{y}\right],$$

where p^f is the average cost of production per hectare, y^h is the historically insured average yield, and η is the MPCI coverage level. In MPCI, if the realized yield is less than the insured yield, an indemnity is paid equal to the difference between the actual yield and the insured yield (a percentage of average of historical yield), multiplied by a pre-agreed value of *sum insured* per unit of yield (Bryla-Tressler et al., 2011). For AUTP, the sum insured is determined based on the average cost of production per hectare (projected value) (Pasaribu and Sudijanto, 2013). Parallel with AUTP, the average cost of production per hectare is used to determine the sum insured for this crop insurance model. The actuarially-fair premium rate (ϕ) is determined as the expected indemnity payment:

$$\phi = \int MPCIi(\tilde{\varepsilon})\, dG(\tilde{\varepsilon}),$$

where $G(\tilde{\varepsilon})$ is the cumulative distribution function of the stochastic yield.

The net benefit (π) that rice farmers receive is the sum of total revenue and MPCI indemnity payments minus the government subsidized (σ) premium rate and total costs, all multiplied by planted acres (a):

$$\pi(l,x;\tilde{\varepsilon}) = (TR(\tilde{\varepsilon}) + MPCIi(\tilde{\varepsilon}) - (1-\sigma)\phi - TC)\, a.$$

Thus, the farmer's problem is to choose inputs to production (l,x) such that expected utility (EU) from profits is maximized:

$$\max_{l,x} EU = \max_{l,x} \int U[\pi(l,x;\tilde{\varepsilon})]\, dG(\tilde{\varepsilon}), \tag{3.2}$$

where $U[\pi] = 1 - \exp[-\beta(\pi)^{\theta}]$ is the Expo-Power utility function, β is the coefficient of risk aversion and $\theta < 1$ is the decreasing absolute risk aversion (DARA) coefficient, respectively.[1] Moreover, the certainty equivalent CE is calculated to find the impact of different policies on

[1] Also note that for the Expo-Power utility function defined here, $\theta = 1$ implies constant absolute risk aversion and $\theta > 1$ implies increasing absolute risk aversion.

the farmer:

$$CE = U^{-1}(EU), \tag{3.3}$$
$$= \left(\frac{\log(1-EU)}{\beta}\right)^{1/\theta}. \tag{3.4}$$

The certainty equivalent converts optimal utility in to a dollar per hectare and measures the amount of money farmers are willing to except to eliminate the risks.

3.2 Theoretical Analysis of Coupling, Wealth, and Insurance Effects

The conceptual analysis in this chapter decomposes the impacts of key MPCI policy parameters (coverage level η and premium subsidy rate σ) into their coupling, wealth, and insurance effects following Hennessy (1998). For tractability, the production function is simplified by only allowing for one input to production m which is a composite of l and x and yields the maximization problem

$$\max_m \int U\left[\pi\left(m;\tilde{\varepsilon},\psi\right)\right]dG\left(\tilde{\varepsilon}\right), \tag{3.5}$$

where ψ is a policy variable that represents the coverage level η and subsidy level σ.

First order condition is

$$\int U_\pi\left[\pi\left(m;\tilde{\varepsilon},\psi\right)\right]\pi_m\left(m;\tilde{\varepsilon},\psi\right)dF\left(\tilde{\varepsilon}\right) = 0. \tag{3.6}$$

To analyze the impact of a small change in the policy parameter ψ input use m, totally differentiate the first-order condition

$$\int\left(U_{\pi\pi}\left[\cdot\right]\pi_m\left(\cdot\right)\pi_m\left(\cdot\right) + U_\pi\left[\cdot\right]\pi_{mm}\left(\cdot\right)\right)dF\left(\varepsilon\right)dm -$$
$$\int\left(A\left[\cdot\right]\pi_\psi\left(\cdot\right)U_\pi\left[\cdot\right]\pi_m\left(\cdot\right) - U_\pi\left[\cdot\right]\pi_{m\psi}\left(\cdot\right)\right)dF\left(\varepsilon\right)d\psi = 0$$

where $A\left[\cdot\right] = -\frac{U_{\pi\pi}\left[\cdot\right]}{U_\pi\left[\cdot\right]}$ is the absolute risk-aversion function. Solving for a change in the composite input for a change in a policy variable yields

$$\frac{dm}{d\psi} = -\frac{1}{\omega}\int U_\pi\left[\cdot\right]\pi_{m\psi}\left(\cdot\right)dF\left(\tilde{\varepsilon}\right) + \frac{1}{\omega}\int U_\pi\left[\cdot\right]A\left[\cdot\right]\pi_\psi\left(\cdot\right)\pi_m\left(\cdot\right)dF\left(\tilde{\varepsilon}\right) \tag{3.7}$$

where $\omega = \int (U_{\pi\pi}[\cdot]\,\pi_m(\cdot)\,\pi_m(\cdot) + U_\pi[\cdot]\,\pi_{mm}(\cdot))\,dF(\tilde{\varepsilon}) < 0$. The sign of $\dfrac{dm}{d\psi}$ is ambiguous, however we can gain further insight into the impact of the policy variables on composite input use by breaking Equation (3.7) into three separate outcomes: the coupling, wealth, and insurance effects. The coupling effect is characterized by the first term on the right-hand-side of Equation (3.7):

$$-\frac{1}{\omega}\int U_\pi[\cdot]\,\pi_{m\psi}(\cdot)\,dF(\tilde{\varepsilon}). \tag{3.8}$$

The key feature of the coupling effect is that a farmer can influence the size of the government payment through input uses, which implies that $\pi_{m\psi}(\cdot) \neq 0$. Since $-\dfrac{1}{\omega}$ and marginal utility $U_\pi[\cdot]$ are both positive, the sign of $\pi_{m\psi}(\cdot)$ dictates the sign of the coupling effect and thus the effect of ψ on input use.

The second term on the right-hand-side of Equation (3.7), contains both the wealth and insurance effects:

$$\frac{1}{\omega}\int A[\cdot]\,\pi_\psi(\cdot)\,U_\pi[\cdot]\,\pi_m(\cdot)\,dF(\tilde{\varepsilon}). \tag{3.9}$$

Integration by parts is applied to separate these two effects. First, redefine the first two terms of the integrand as $J(\cdot,\tilde{\varepsilon}) \equiv A[\cdot]\,\pi_\psi(\cdot)$. Then, Equation (3.9) can be written as

$$\Psi \equiv \frac{\int J(\cdot,\tilde{\varepsilon})\,U_\pi[\cdot]\,\pi_m(\cdot)\,dF(\tilde{\varepsilon})}{\omega}. \tag{3.10}$$

Let $u = J(\cdot,\tilde{\varepsilon})$ and $dv = U_\pi[\cdot]\,\pi_m(\cdot)\,dF(\tilde{\varepsilon})$, then $du = J'(\cdot,\tilde{\varepsilon})$ and $v = \int U_\pi[\cdot]\,\pi_m(\cdot)\,dF(\tilde{\varepsilon})\,d\tilde{\varepsilon}$. Applying the integral by parts formula to the numerator of Equation (3.10) and multiplying both sides by ω yields

$$\Psi\omega = J(\cdot,\tilde{\varepsilon})\int U_\pi[\cdot]\,\pi_m(\cdot)\,dF(\tilde{\varepsilon}) - \int\int U_\pi[\cdot]\,\pi_m(\cdot)\,dF(\tilde{\varepsilon})\,J'(\cdot,\tilde{\varepsilon})\,d\tilde{\varepsilon},$$

where

$$J'(\cdot,\tilde{\varepsilon}) = A_\pi[\cdot]\,\pi_{\tilde{\varepsilon}}(\cdot)\,\pi_\psi(\cdot) + A[\cdot]\,\pi_{\psi\tilde{\varepsilon}}(\cdot). \tag{3.11}$$

At the optimal input use, $\int U_\pi[\cdot]\,\pi_m(\cdot)\,dF(\tilde{\varepsilon})=0$ from the first-order condition given in Equation (3.6), then

$$\Psi\omega=-\int\int U_\pi[\cdot]\,\pi_m(\cdot)\,dF(\tilde{\varepsilon})\,J'(\cdot,\tilde{\varepsilon})\,d\tilde{\varepsilon}.$$

Following Hennessy (1998), assume an increase in production leads to higher risk $\pi_{m\tilde{\varepsilon}}(\cdot)\geq 0$, which implies that $\int U_\pi[\cdot]\,\pi_m(\cdot)\,dF(\tilde{\varepsilon})\leq 0$. Therefore, because $\omega<0$, $\Psi\omega$ is positive, implying input use increases, if $J'(\cdot,\nu)\leq 0$. Thus, determining the sign of $J'(\cdot,\nu)$ is vital in assessing the directional impact of policy parameters on input use through the wealth and insurance effects.

In Equation (3.11), the first term is the wealth effect and the second term is the insurance effect, which are key in determining the impact of a policy variable on input use. For the wealth effect, $A_\pi[\cdot]<0$ for DARA utility. Thus, if $p>p^f$, then $\pi_{\tilde{\varepsilon}}(\cdot)=\overbrace{\left(p-p^f\right)\tilde{y}_{\tilde{\varepsilon}}(m)}^{+}\overbrace{-(1-\sigma)\,\phi_{\tilde{\varepsilon}}^{MPCI}(m)}^{-}$ and the impact of the wealth effect on input use is ambiguous. However, if $p<p^f$, then $\pi_{\tilde{\varepsilon}}(\cdot)=\overbrace{\left(p-p^f\right)\tilde{y}_{\tilde{\varepsilon}}(m)}^{-}\overbrace{-(1-\sigma)\,\phi_{\tilde{\varepsilon}}^{MPCI}(m)}^{-}<0$ and the impact of the wealth effect on input use is negative (positive) if $\pi_\psi(\cdot)<0$ ($\pi_\psi(\cdot)>0$). For the insurance effect, $A[\cdot]>0$ and impact on input use is positive (negative) if $\pi_{\psi\tilde{\varepsilon}}(\cdot)<0$ ($\pi_{\psi\tilde{\varepsilon}}(\cdot)>0$). Table 3.1 summarizes the results of the comparative statics, which are discussed next.

Table 3.1: Comparative Statics of Policy Parameters

Policy	Parameter	Coupling	Wealth		Insurance	Total
			$p>p^f$	$p<p^f$		
MPCI	Coverage level (η)	0	?	?	$+$	?
	Premium subsidy (σ)	$-$	?	$-$	$-$	?

3.2.1 Coupling Effect of η and σ

The effect of policy variables, η and σ, on input use through the coupling effect is presented here. Because the yield guarantee (coverage level time the historical yield ηy^h) does not depend on input use, no coupling effect exists for the coverage level η. More formally, because $\phi_m^{MPCI}(m) = \int p^f \tilde{y}(m)\, dG(\tilde{\varepsilon})$ and $\phi_{m\eta}^{MPCI}(m) = 0$, then

$\pi_{m\eta}(\cdot) = -(1-\sigma)\,\phi_{m\eta}^{MPCI}(m) = 0$ and no coupling effect exists for changes in the coverage level.

However, because the premium subsidy is multiplicative with the premium rate which depends on input use, a coupling effect exists for σ and farmers can impact the size of their payments by adjusting inputs and thus yield. Specifically, since $\phi_m^{MPCI}(m) = -\int p^f \tilde{y}_m(m)\, dG(\tilde{\varepsilon}) < 0$, then $\pi_{m\sigma}(\cdot) = \phi_m^{MPCI}(m) < 0$. Consequently, higher subsidies lower premium costs to farmers which incentivizes farmers to reduce input use to collect higher net insurance payments.

3.2.2 Wealth Effect of η and σ

This subsection provides the conceptual framework on how the policy variables affect input use through the wealth effect. Note that, as discussed above, if $p > p^f$ then the wealth effect is ambiguous, and the impact of a small change in either policy variable is either positive or negative depending on other market conditions. If $p < p^f$, then the wealth effect may be determined. For the coverage level, $\pi_\eta(\cdot) = p^f y^h - (1-\sigma)\,\phi_\eta^{MPCI}(m)$ is ambiguous because the first term on the right-hand-side $\left(p^f y^h\right)$ is positive and the second term on the right-hand-side $\left(-(1-\sigma)\,\phi_\eta^{MPCI}(m)\right)$ is negative since $\phi_\eta^{MPCI}(m) = \int p^f y^h g(\tilde{\varepsilon})\, d\tilde{\varepsilon} > 0$. Therefore, the impact of η on input use through the wealth effect is also indeterminate. However, a marginal increase in the subsidy level reduces input use as $\pi_\sigma(\cdot) = \phi^{MPCI}(m) > 0$.

3.2.3 Insurance Effect of η and σ

This subsection provides the analysis on how policy variables affect input use through the insurance effect. For the coverage level, the insurance effect is positive because

$\pi_{\eta\tilde{\varepsilon}}(\cdot) = -(1-\sigma)\,\phi_{\eta\tilde{\varepsilon}}^{MPCI}(m) < 0$ since $\phi_{\eta\tilde{\varepsilon}}^{MPCI}(m) = p^f \eta y^h g(\tilde{\varepsilon}) > 0$. Therefore, an increase in the coverage level will result in the farmer using more inputs. However, the insurance effect for the subsidy rate is negative because $\pi_{\sigma\tilde{\varepsilon}}(\cdot) = \phi_{\tilde{\varepsilon}}^{MPCI}(m) > 0$

given that $\phi_{\tilde{\varepsilon}}^{MPCI}(m) = p^f \left(\eta y^h - \tilde{y}(m)\right) g(\tilde{\varepsilon}) > 0$ since $\eta y^h - \tilde{y}(m) \geq 0$ for an indemnity payment to be made. Thus, higher subsidy levels cause the farmer to reduce input use.

Chapter 4. Numerical Analysis

To quantify the direction and magnitude of the impact of the coverage level and premium subsidy, the model given by Equation (3.2) is calibrated to an average rice farmer in Tuban Regency in Indonesia and then numerically optimized to analyze changes in the policy parameters. The first section in this chapter discusses data sources, the estimation of the yield distribution, and the calibration of the remaining parameters. The second section discusses the simulation and results, and the final section provides conclusions and recommendations.

4.1 Data, Yield Distribution, and Calibration

The analysis here focuses on the Tuban Regency which is located in the northern part of East Java Province, one of the largest Indonesian rice producing provinces. The Tuban Regency can be found 675 kilometers east of Jakarta and 101 kilometers northwest of Surabaya which is the capital of the East Java Province. The size of Tuban Regency is about 1839.94 square kilometers with a population in 2014 of around 1.3 million (BPS-Statistic of Tuban Regency, 2015b). Like many other places in Indonesia, the climate in Tuban is tropical with an average rainfall of about 2,277 millimeters per year. Crops mainly grown in the area are rice and casava. In Tuban, the average household comprises of four or five persons and it owns 0.1 - 0.5 Ha of arable land.

4.1.1 Data

Yearly yield data from 1979 to 2014 for the Tuban Regency are collecting from Statistics of Tuban Regency (BPS-Statistic of Tuban Regency, 2015a). Data on the value of production and cost of production per hectare per planting season of wetland paddy, which are used to calculate the market price and input prices, are available from the Statistic of East Java Province (BPS East Java, 2015).

4.1.1.1 Detrending and Correcting for Heteroskedasticity

Before estimating the yield distribution, the yield data are detrended to account for technology changes over time. Several methods for detrending exist. This thesis follows Tejeda et al. (2008) and uses two time regressors, one linear and one squared, to detrend the Tuban yield data. We correct for heteroskedasticity in the data. Heteroskedasticity is the term used when the scatter of the errors is non-constant over the range of the independent variable. Heteroskedasticity is a concern because it can lead to bias in parameter estimates. Therefore, correcting heteroskedasticity in the data is imperative in order to provide a factual estimated densities. adopt previous literatures (Ramadan, 2011; Tejeda et al., 2008) which applied the following method to detrend and correct heteroskedasticity in the yield data. First, we calculate the estimated error by taking the difference between the actual yield and the estimated yield from regressing the yield data on the linear and squared time trend regressors:

$$\hat{e}_t = y_t - \hat{y}_t$$

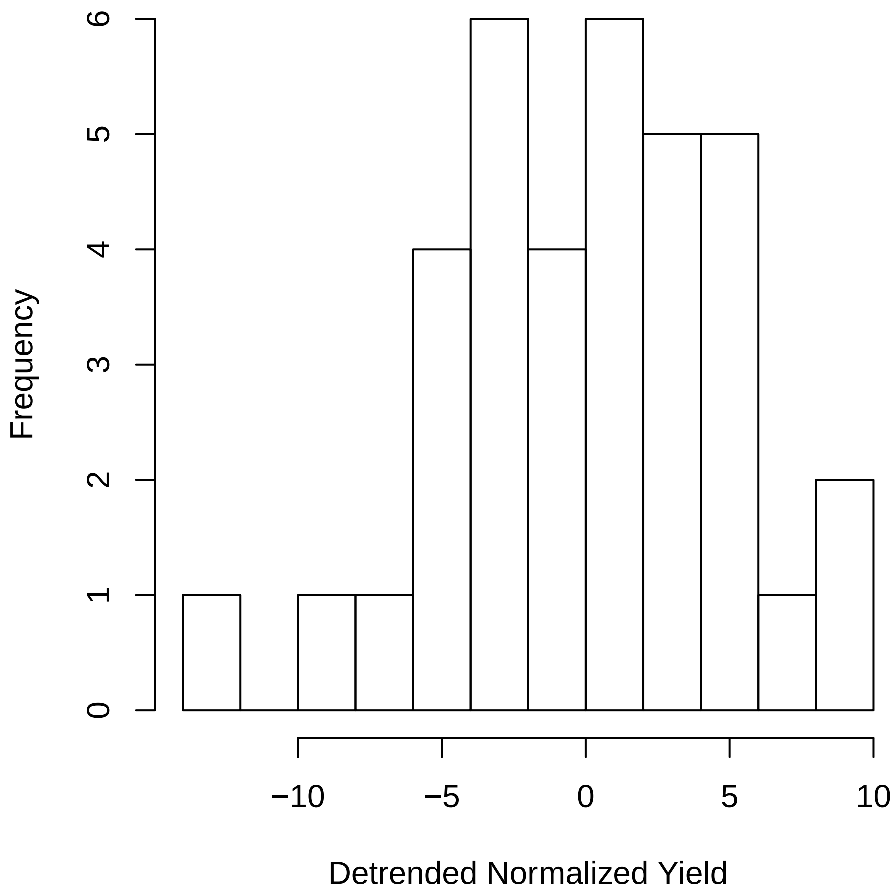
where $\hat{y}_t = \hat{\beta}_0 - \hat{\beta}_1 t - \hat{\beta}_2 t^2$, $\hat{\beta}_i$s are estimated parameters, and $t = 1, 2, ..., T$ is a linear time trend. Then detrended yield $\tilde{y}_t$ is calculated as

$$\tilde{y}_t = y_T (1 + \frac{\hat{e}_t}{y_t}),$$

where y_T is the yield data for the last data year 2014 and y_t is the yield data ranging from 1974-2014.

Next, we transform the county data into farm-level data by additional disturbance to the variance of the regency yield data. When evaluating insurance indemnity payment and premiums, it is crucial to obtain accurate estimates of farm-level yield probability density functions (PDF) (Xu, 2004). However, due to an insufficient time trend in farm-level yield data, crop yield PDF's are not possible to estimate accurately. To address this problem, Goodwin (2009) assumes a farm versus county or farm versus State yield relationship that appears reasonable by adding additional variance to county data that is normally distribution $N(0, \sigma)$, where σ is

Figure 4.1: Histogram of Detrended Yield Data



75% of the standard deviation of the detrended state average yield. Therefore, this thesis uses such method to obtain parameters of farm-level yield.

Based on the production function specification Equation (3.1) in Chapter 3, the $\tilde{\varepsilon}$ is an additive term representing yield randomness that has a mean of zero. Therefore, to estimate $\tilde{\varepsilon}$, the detrended yield data are normalized by subtracting the mean detrended yield. This results in a disturbance term that is consistent with the theoretical model. See figure 4.1 for a histogram of detrended yield data for Tuban.

4.1.2 Yield Distribution

Parametric and nonparametric methods are the two main techniques used to estimate a density. However, this thesis will focus only on parametric methods due to the availability of the data. We include normal distribution since Just and Weninger (1999) consider such distribution as an empirical distribution for studying crop insurance programs and production under uncertainty. Moreover, the skew normal distribution is also considered in this thesis because yield data is often found to be non-symmetrical. The skew normal distribution has a shape parameter that regulates the skewness, which can account for a continuous variation from normality to non-normality.

4.1.2.1 Normal Distribution

Using the detrended yield data described in section 4.1.1.1, this section estimates normal distributions by applying a maximum likelihood estimation method. The density function of a normal distribution with mean $\mu \in (-\infty,\infty)$ and standard deviation $\sigma > 0)$ is given by

$$f(\tilde{y}|\sigma,\mu) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left[-\frac{(\tilde{y}-\mu)^2}{2\sigma^2}\right],$$

where a support of $\tilde{y} \in (-\infty,\infty)$. The parameters are estimated using the Maximum Likelihood estimator (ML). Therefore, based on an i.i.d. random sample, the likelihood function is

$$L(\sigma,\mu|\tilde{y}_1,...,\tilde{y}_T) = \sigma^{-n}(2\pi)^{-n/2}\exp\left[-\frac{1}{2\sigma^2}\sum_{t=1}^{T}(\tilde{y}_t-\mu)^2\right],$$

and the log-likelihood is given by

$$l(\sigma,\mu|\tilde{y}_1,...,\tilde{y}_T) = -\frac{n}{2}\ln(2\pi) - \frac{n}{2}\ln(\sigma^2) - \frac{1}{2\sigma^2}\sum_{t=1}^{T}(\tilde{y}_t-\mu)^2.$$

Given the detrended yield data, maximum likelihood estimates σ and μ

that optimizes $l(\sigma,\mu|\tilde{y}_1,...,\tilde{y}_T)$. This optimization is performed numerically using the R software using the “nlm” Newton-type algorithm. Table 4.1 displays the parameter estimates for the normal distribution.

Table 4.1: Normal PDF: Parameter Estimates

Parameter	
Mean	0.000
Standard deviation	4.633

4.1.2.2 Skew Normal Distribution

Using the same data from section 4.1.1.1, we also estimate the skew normal distribution by applying a maximum likelihood estimation method. The skew-normal distribution with location ε, scale $\omega > 0$, and asymmetry λ parameters, which was introduced by Azzalini (1985), is

$$f(\tilde{y}|\varepsilon,\omega,\lambda) = \frac{2}{\omega}\phi\left(\frac{\tilde{y}-\varepsilon}{\omega}\right)\Phi\left(\lambda\frac{\tilde{y}-\varepsilon}{\omega}\right),$$

where ϕ is the density function of the normal distribution and Φ is the cumulative distribution function of the normal distribution. We estimate the parameters by using Maximum Likelihood methods (ML). Therefore, based on an independent and identical distribution random (i.i.d.) sample, the likelihood function is

$$L(\varepsilon,\omega,\lambda|\tilde{y}_1,...,\tilde{y}_T) = \prod_{t=1}^{T}\frac{2}{\omega}\phi\left(\frac{\tilde{y}_t-\varepsilon}{\omega}\right)\Phi\left(\lambda\frac{\tilde{y}_t-\varepsilon}{\omega}\right),$$

and the log-likelihood is given by

$$l(\varepsilon,\omega,\lambda|\tilde{y}_1,...,\tilde{y}_T) = n\log\frac{2}{\omega} + \sum_{i=1}^{n}\log\phi(\frac{\tilde{y}_t-\varepsilon}{\omega}) + \sum_{i=1}^{n}\log\Phi(\lambda\frac{\tilde{y}_t-\varepsilon}{\omega}).$$

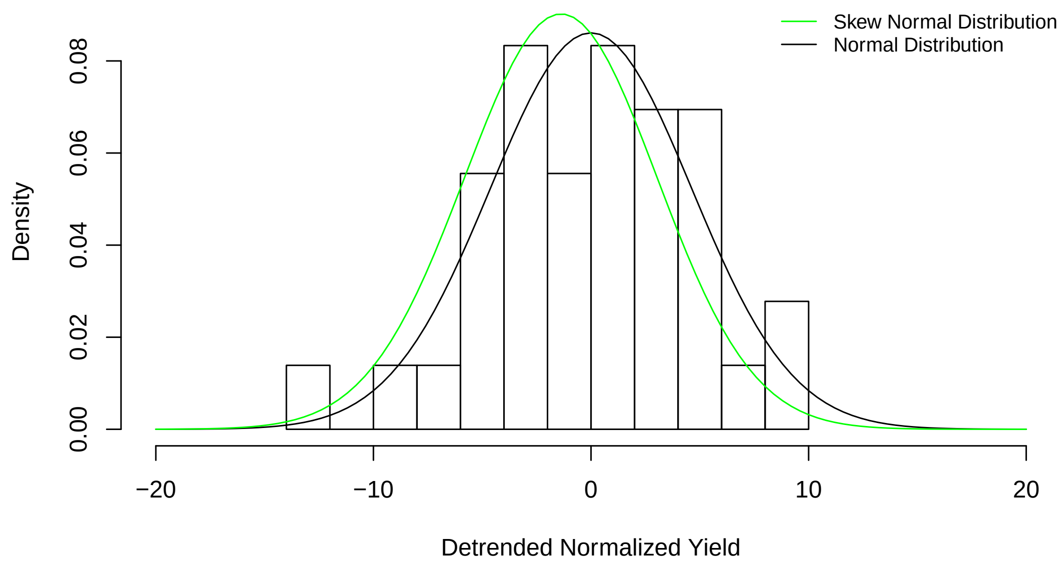
With the detrended yield data, maximum likelihood estimates ε, ω and λ

which optimizes $l(\varepsilon,\omega,\lambda|\tilde{y}_1,...,\tilde{y}_T)$. As with the normal distribution, this optimization is perform numerically using the R software using the "nlm" Newton-type algorithm. Table 4.2 provides the parameter estimates for the estimated distribution.

Table 4.2: Skewed Normal PDF: Parameter Estimates

Parameter	
Mean	0.013
Standard deviation	4.650
Gamma	-0.415

Figure 4.2: Plot Skew and Normal Distribution over the Histogram



4.1.2.3 Goodness of Fit Tests

Figure 4.2 plots the histogram of the detrended normalized yield data and the normal and skewed normal density functions based on the MLE parameter estimates. Because skewed normal density is off center of the normal density, this figure suggests that the yield data are positively skewed. Next, more formal goodness of fit tests are presented in order to determine which model suitably fits the data. Three goodness of fit tests are used to analyze the model selection for skew normal distribution and normal distribution: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Cumulative Delta.

AIC and BIC assess the goodness of fit term by weighing model precision against the number of parameters. This analysis thus evaluates the statistical relevance of additional precision of more parameters. The formula for AIC and BIC are given by $AIC_i = -2\log(L_i) + 2k_i$ and $BIC_i = -2\log(L_i) + k_i \log(n)$, where k_i is the number of parameters in the i^{th} distribution, L_i is the value of the maximized likelihood function evaluated at the estimated parameters, and n is the number data points. By construction, the lowest AIC and BIC values give the most accurate distribution without over fitting. Cumulative Delta, on the other hand, evaluates a distance between the empirical distribution function and the theoretical distribution function. We compare the cumulated delta (the cumulative sum of the absolute values of the difference between the empirical and the theoretical distribution functions) between the two models. The model with the lowest cumulative sum is the better suited parameterization.

Table 4.3 reports the results of AIC and BIC. The result of the AIC test for skew normal distribution is higher compared to that of normal distribution. This indicates that, based on AIC, the skew normal distribution less preferable than normal distribution. However, the AIC result is contradicted to the BIC result where the skew normal distribution performs better than normal distribution because skew normal has a low BIC score. Similarly, Figure 4.3 graphical shows that the cumulative delta for the skew normal distribution is lower than that of the normal distribution. This indicates that skew normal distribution performs better than the normal distribution. Given the smaller BIC and cumulative delta of the skew normal distribution, this distribution is the better suited parameterization of the Tuban yield size distribution and is used in the analysis below.

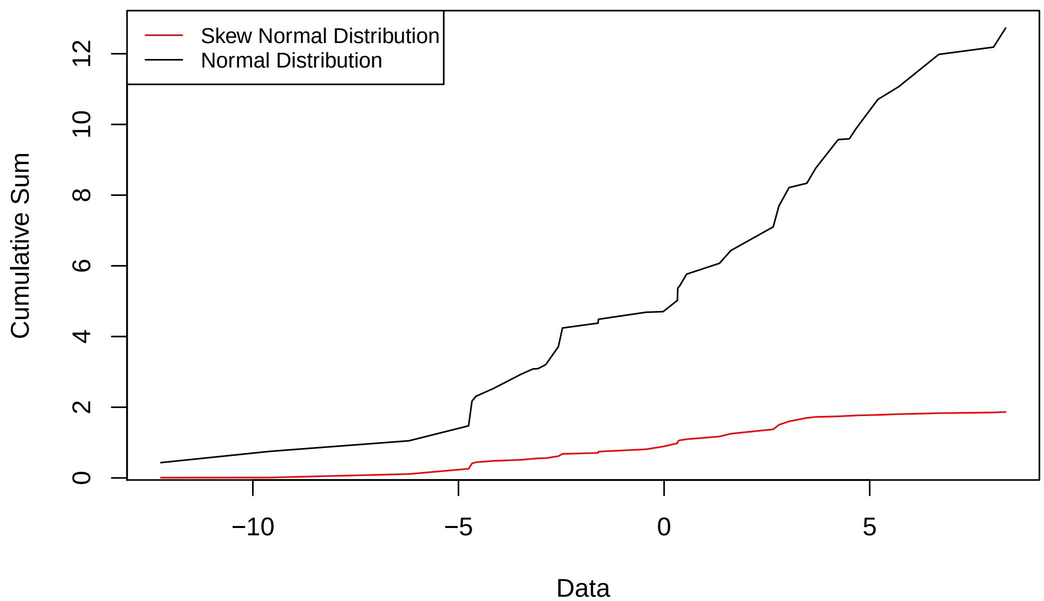
Table 4.3: Goodness of Fit Result

Distribution	AIC	BIC
Skew Normal	217.70	213.08
Normal	216.56	213.48

4.1.3 Calibration

Now that the yield density is estimated, we calibrate the remaining parameters in the model for the simulation analysis. The Expo-Power utility function $U[\pi] = 1 - \exp[-\beta(\pi)^{\theta}]$ is applied to calculate farmers' expected utility, where β is the coefficient of risk aversion, $\theta < 1$ is the DARA coefficient (Saha et al., 1994). Based on Love and Buccola (1991) and Saha et al. (1994), this parameter ranges from 0.5 to 2.7. We assume a risk aversion coefficient of $\beta = 1$, which is within the range suggested by Love and Buccola (1991) and Saha et al. (1994). Moreover, since there is no literature on DARA utility for Indonesian rice farmers,

Figure 4.3: Cumulated Delta



this thesis utilizes U.S. farmers' DARA utility researched by Saha et al. (1994) which suggests $\theta = 0.4$.

The production function used is $\tilde{y} = zl^{\alpha_l}x^{\alpha_x} + \tilde{\varepsilon}$ where l is labor, x is a composite of intermediate inputs and capital, α_l and α_x are share parameters with $\alpha_l + \alpha_x \leq 1$, and the total cost is $TC = wl + rx$. Using the 2014 rice yield in Tuban regency and the data from BPS East Java (2015), we calculate data on the market price per quintal metrics(p), the composite price for intermediate inputs (r), and the price of labor (w). The share parameters for the production function are calculated by utilizing value of inputs and total production data. The share parameters of α_l and α_x are calculated by dividing the value input costs with the value of production. Given share parameters, input data, and assuming $\tilde{\varepsilon} = 0$ implying an average year, the productivity parameter (z) is calibrated by performing a grid search over z to match the 2014 yield data.

Next, parameters of the government policy on MPCI are provided. For average cost of production per hectare (p_f), we use the total cost of production in 2014 because such data are the latest data provided by the statistics of East Java Province. The historical insured average yield (y_h) is taken from the mean yield for the last five years (2010-2015) which is parallel to the computation regulated by the U.S. Department of Agriculture (four to ten years) (Edwards and Hofstrand, 2003). All the parameters used for the simulation analysis are summarized in Table 4.4. Finally, as elaborated in the subsequent section, this thesis specifies several scenarios on different coverage levels η (10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%) and subsidy levels σ (5%, 10%, 15%, 20%, 25%).

Table 4.4: Calibrated Parameters for the Model

Parameters	Value
Input and Output Price	$p = 21.77$
	$p_w = 7.85$
	$p_x = 3.41$
Production Function	$\alpha_l = 0.48$
	$\alpha_x = 0.21$
	$z = 2.79$
Indemnity payment in MPCI	$p_f = 16.08$
	$y_h = 64.31$
Utility Function	$\beta = 1$
	$\theta = 0.4$

4.2 Simulation and Results

To quantify the impacts of MPCI Insurance on Indonesian rice farmers, we numerically optimized the model expected utility given in Equation (3.2). This simulation analysis consists of the baseline and several MPCI policy scenarios (changing in coverage levels and premium subsidies). The baseline scenario, consistent with the calibration of the model, is performed without MPCI insurance in place. Thus, in the baseline, the farmer is fully exposed to all risk. To consider a wide range of policy options, the alternate scenarios comprises of five different premium subsidies (σ) and nine different coverage level (η). We increase the premium subsidies from 5% to 25% and coverage level from 10% to 90%. Next, we compare the policy scenarios and baseline simulation results to quantify the impacts of MPCI Insurance on labor, composite of variable input, output, expected indemnity, premium payment, and certainty equivalent.

Tables 4.5 and 4.6 report the results for labor and the composite input used in Indonesian rice farming. The baseline simulation indicates that the optimal input use for labor and composite input without applying MPCI insurance is \$85.485 and \$85.434 per Ha, respectively, meaning that when the insurance program is not in place the optimal amount of money that farmers will pay for labor and composite input are \$85.485 and \$85.434 per Ha, respectively. The labor and composite input use remain constant when the premium subsidies are increased to 25% and the coverage level are raised to 30% because, for these very low coverage levels, the farmer does not expect to receive any indemnity payment. With no expected payment, the farmer does not alter their optimal input use. However, for coverage levels at or above 40%, the farmer expects indemnity payments, which triggers a reduction in input use as the farmer tries to maximize both insurance payments and market revenue simultaneously. This highlights the moral hazard on MPCI crop insurance. Intuitively, for non-zero expected indemnity payment (i.e., coverage levels above 40%) the lower coverage level leads to a larger reduction in input use than the higher coverage level, because at farmers are incentivised to lower inputs, and thus yield, in order to receive larger indemnity payments. With higher coverage levels, farmers are more likely to received an indemnity payment and thus have less incentive to reduce input use to receive payments. As the subsidy level increases, farmers earn more revenue from crop insurance relative to market revenue, which the farmer takes advantage of by reducing input use to increase the size of the indemnity payments.

The input use for labor reduces by 73% when the coverage level is increased to 40% while holding the premium subsidy constant in 25% (Table 4.5). The lowest reduction (15%) takes place when we eliminate the premium subsidy and raise the coverage level to 90%. The highest decrease of the composite of variable inputs (73%) also happens when the coverage level and subsidy are increased to 40% and to 25%, respectively. The composite of variable input drops slightly (15%) when the premium subsidy is removed and the coverage level of 90% is implemented (Table 4.6). In this case, farmers can set up the input use in order to lower the production and get more insurance payment. Based on the table results, providing small premium subsidy with high coverage level, such as imposing subsidy of less than 15 % and and coverage level of higher than 70%, may more preferable to reduce the moral hazard since the reduction of the input uses will be less than 40% if such policy applied. These input results are consistent with the theoretical findings summarized in Table 3.1 where an increase in the coverage level will increase input use through the insurance effect and an increase in the subsidy will decrease input use through the coupling, wealth, and insurance because $p < p^f$.

Table 4.5: Impact on Labor \$/Ha

		Subsidy levels, σ					
		0%	5%	10%	15%	20%	25%
Coverage Levels η	0%	85.458	85.458	85.458	85.458	85.458	85.458
	10%	85.458	85.458	85.458	85.458	85.458	85.458
	20%	85.458	85.458	85.458	85.458	85.458	85.458
	30%	85.458	85.458	85.458	85.458	85.458	85.458
	40%	23.526	23.421	23.317	23.185	23.059	22.873
	50%	32.063	31.919	31.775	31.600	31.373	31.086
	60%	41.375	41.187	40.940	40.662	40.256	39.583
	70%	51.297	51.032	50.702	50.175	48.926	43.225
	80%	61.831	61.378	60.679	57.710	50.116	43.226
	90%	72.716	71.731	66.143	57.741	50.116	43.227

Table 4.6: Impact on Composite of Variable Inputs

		Subsidy levels, σ					
		0%	5%	10%	15%	20%	25%
Coverage Levels η	0%	85.434	85.434	85.434	85.434	85.434	85.434
	10%	85.434	85.434	85.434	85.434	85.434	85.434
	20%	85.434	85.434	85.434	85.434	85.434	85.434
	30%	85.434	85.434	85.434	85.434	85.434	85.434
	40%	23.524	23.418	23.311	23.183	23.041	22.867
	50%	32.054	31.909	31.766	31.599	31.365	31.082
	60%	41.363	41.181	40.929	40.650	40.256	39.573
	70%	51.285	51.020	50.688	50.156	48.912	43.213
	80%	61.813	61.359	60.660	57.694	50.102	43.214
	90%	72.695	71.711	66.125	57.724	50.102	43.213

Next, we discuss the impacts of MPCI insurance on expected output reported in Table 4.7. The baseline output is consistent with the scenario output as the premium subsidy is increased to 25% and the coverage level is boosted to 30%. Parallel with the input use, the reduction in the output also only appears when the coverage levels is at 40% and above. The output reduction is about 60% with a premium subsidy of 25% and a coverage level of 40% are imposed. However, output only declined by about 10% if the coverage level is increased to 90% without any premium subsidy. Thus, regulating small premium subsidy with high coverage level is a possible solution to minimizing moral hazard in MPCI insurance. Table 4.7 implies a similar result as Table 4.5 and Table 4.6 where imposing a subsidy of less than 15% and coverage level of higher than 70% are more propitious. The impact of changes in the coverage level and premium subsidy on output are consistent with the input results which conform to the theoretical findings in Table 3.1.

Table 4.7: Expected Output: Qu/Ha

		Subsidy levels, σ					
		0%	5%	10%	15%	20%	25%
Coverage Levels η	0%	63.111	63.111	63.111	63.111	63.111	63.111
	10%	63.111	63.111	63.111	63.111	63.111	63.111
	20%	63.111	63.111	63.111	63.111	63.111	63.111
	30%	63.111	63.111	63.111	63.111	63.111	63.111
	40%	25.565	25.485	25.405	25.305	25.205	25.065
	50%	31.756	31.656	31.556	31.436	31.276	31.076
	60%	37.967	37.847	37.687	37.507	37.247	36.808
	70%	44.138	43.978	43.778	43.458	42.698	39.149
	80%	50.308	50.050	49.650	47.935	43.423	39.149
	90%	56.361	55.825	52.742	47.953	43.423	39.149

Results for expected indemnity, calculated as $\int MPCIi(\tilde{\varepsilon})\,dG(\tilde{\varepsilon})$, are reported in Table 4.8. As discussed above, for coverage levels at 30% and below the farmer does not receive any indemnity payments. However, for coverage levels above 30%, increasing both the premium subsidy and coverage level leads to incremental increases in expected indemnity. The lowest expected indemnity ($7.784/Ha) is collected in the scenario where the premium subsidy is eliminated but the coverage level is 40%. Whereas, the highest expected indemnity

($301.221/Ha) is obtained in the scenario where the premium subsidy and coverage level are both at their highest level of 25% and 90%, respectively.

Table 4.8: Expected Indemnity ($/Ha)

		Subsidy levels, σ					
		0%	5%	10%	15%	20%	25%
Coverage Levels η	0%	0	0	0	0	0	0
	10%	0	0	0	0	0	0
	20%	0	0	0	0	0	0
	30%	0	0	0	0	0	0
	40%	7.784	8.529	9.314	10.350	11.445	13.071
	50%	10.138	11.221	12.361	13.799	15.826	18.515
	60%	12.595	14.046	16.088	18.515	22.221	28.858
	70%	15.826	17.965	20.771	25.497	37.364	94.388
	80%	19.373	23.103	29.175	56.518	129.073	197.800
	90%	24.893	33.177	82.644	159.652	232.493	301.221

Table 4.9 informs the results for expected MPCI payment to farmer, calculated as $\int [MPCIi(\tilde{\varepsilon}) - (1-\sigma)\phi]\, dG(\tilde{\varepsilon}) = \sigma\phi$. Note that when the subsidy rate is zero, the expected indemnity payment is exactly equal to the premium, and the expected payment to the farmer is zero (first column in Table 4.9). For coverage levels above 30% and subsidy level greater than zero, the payment to the farmer is equal to the subsidy rate time the premium rate ($\sigma\phi$). The table shows that as the subsidy and coverage level increase, the higher the insurance payments the farmers receive. That is for a coverage level of 40% and subsidy of 5%, the farmer will received on average an insurance payment of $0.426/Ha. However, with a coverage level of 90% and subsidy of 25%, the farmer will receive an average insurance payment of $75.305/Ha.

Table 4.10 presents the results for the certainty equivalent calculated from Equation (3.4). The certainty equivalent at the baseline is $80.546/Ha. The addition of subsidy levels result in no change of certainty equivalent until the coverage level increases to 40%. Therefore, the farmers will be better off by increasing coverage level to 40% and above. The results show that the farmers prefer the highest coverage level for each of the subsidy levels. Furthermore, the highest certainty equivalent is obtained when the subsidy level and the coverage level are

Table 4.9: Expected MPCI Payment to Farmer ($/Ha)

Coverage Levels η	Subsidy levels, σ: 0%	5%	10%	15%	20%	25%
0%	0	0	0	0	0	0
10%	0	0	0	0	0	0
20%	0	0	0	0	0	0
30%	0	0	0	0	0	0
40%	0	0.426	0.931	1.552	2.289	3.268
50%	0	0.561	1.236	2.070	3.165	4.629
60%	0	0.702	1.609	2.777	4.444	7.215
70%	0	0.898	2.077	3.825	7.473	23.597
80%	0	1.155	2.918	8.478	25.815	49.450
90%	0	1.659	8.264	23.948	46.499	75.305

increased to 25% and 90%, respectively. Thus, the farmers benefits the most from policy combination under such scenario.

Table 4.10: Certainty Equivalent ($/Ha)

Coverage Levels η	Subsidy levels, σ: 0%	5%	10%	15%	20%	25%
0%	80.546	80.546	80.546	80.546	80.546	80.546
10%	80.546	80.546	80.546	80.546	80.546	80.546
20%	80.546	80.546	80.546	80.546	80.546	80.546
30%	80.546	80.546	80.546	80.546	80.546	80.546
40%	91.770	91.777	91.785	91.793	91.802	91.812
50%	92.431	92.439	92.449	92.459	92.471	92.485
60%	92.932	92.942	92.954	92.968	92.984	93.003
70%	93.299	93.312	93.327	93.344	93.368	93.415
80%	93.550	93.566	93.585	93.614	93.685	93.808
90%	93.697	93.719	93.757	93.848	93.995	94.192

4.3 Conclusions and Recommendation

This section concludes several findings resulting from the simulation and suggests some recommendation relative to the simulation. Based on the certainty equivalent, farmers prefer the highest coverage level. For the 90% coverage level, farmers prefer the highest subsidy level. For expected indemnity, farmers prefer high premium subsidies and high coverage levels. The highest expected indemnity is obtained in the scenario where the premium subsidy and coverage level escalate to 25% and 90%, respectively. Similarly, for insurance payment, farmers receive the highest payment for the largest high coverage level and premium subsidy. Thus, the farmers prefer either high coverage level with small subsidy or small coverage level with high subsidy. Based on the input and output table, MCPI can have substantial moral hazard implications. Farmers can set up the input use in order to lower the production and get more insurance payment. To mitigate the moral hazard, Indonesian government can possibly offer an insurance with high coverage levels and low premium subsidies.

As the result of all findings in the simulation, MPCI insurance with high coverage levels and low premium subsidies is suggested to Indonesian government since such policy benefits both farmers and the insurance provider. Although in certainty equivalent the farmers prefer the highest both coverage levels and subsidy levels, the farmers are still better off if the government only provides small subsidy levels with high coverage levels. In addition, continued collection of yield data is imperative to assess premium rates, especially collecting seasonal rice yield data since Indonesia has two rice planting seasons. The two seasons are for the months October-March and April-September, and the yield variation in each planting season is dissimilar. Normally, the yield data of October-March planting season (wet season) is higher than the yield data of April-September (dry season). Therefore, collecting the yield data for each planting season is necessarily important to calculate more a accurate premium rate.

Chapter 5. Summary and Research Extension

This thesis constructs a model of the yield-based MPCI crop insurance policy for a risk averse rice farmer in Indonesia and presents the comparative statics analyses of the effect of policy variables on yield through the coupling, wealth, and insurance effects. Using yield data from 1979 to 2014 for the Tuban Regency, this study applies numerical optimization to the model and simulate the effects of different coverage and subsidies levels on input use, certainty equivalents, indemnity payment, and premiums. The result from the theoretical analysis indicates that no coupling effect exists for changes in the coverage level, while a coupling effect does exists for change in the premium subsidy implying that farmers can impact the size of their payments by adjusting inputs and thus yield. The analysis for wealth effect, on the other hand, shows several implications. If the market price p is higher than the average cost of production p^f, the wealth effect is ambiguous, and thus the impact of a small change in either policy variable is either positive or negative depending on other market conditions. Moreover, if the market price p is smaller than the average cost of production p^f, then the wealth effect may be determined. The wealth effect for subsidy levels is negative, indicating a marginal increase in the subsidy levels reduces input use. Unlike for the subsidy levels, the wealth effect for the coverage levels is ambiguous. Furthermore, the analysis of the insurance effect for coverage levels shows a positive sign, revealing that an increase in the coverage level will result in the farmer using more inputs. Conflicting with the coverage level, the insurance effect for subsidy levels generates a negative sign, where higher subsidy levels cause the farmer to reduce input use.

The result from the numerical analysis shows that MPCI crop insurance results in moral hazard. At very low coverage levels ($\leq$30%), the farmer does not expect to receive any indemnity payment. However, for coverage levels at or above 40%, the farmer expects indemnity payments, which triggers a reduction in input use as the farmer tries to maximize both insurance payments and market revenue simultaneously. For non-zero expected indemnity payments (i.e., coverage levels above 40%), the lower coverage levels and higher subsidies lead to a larger reduction in input use than the higher coverage level and lower subsidies. Therefore, providing small premium subsidy with a high coverage level may be more preferable to reduce the moral hazard. For certainty equivalent, the result reveals that farmers prefer the highest coverage level. Also, for the 90% coverage level, the results also indicate that farmers prefer the highest subsidy level. For expected indemnity and insurance payment, farmers receive the highest payment for the largest high coverage level and premium subsidy. Thus, at any given subsidy rate, the farmers prefer high coverage level. However, if given the choice, the farmer prefers both the highest coverage level and subsidy rate. To sum up, the numerical analysis results indicate that MPCI insurance with high coverage levels and low premium subsidies is suggested to Indonesian government since such a policy improves the farmers' wellbeing while mitigating moral hazard facing the insurance provider.

The results from this study can be used as empirical evidence to assist the policy makers in the Ministry of Agriculture in implementing MPCI crop insurance in Indonesia. However, future studies such as conducting numerical analysis for Gresik Regency and conducting research on area-based insurance, are highly recommended in order to foster the development of crop insurance in Indonesia. The analysis has several limitations due to data availability that subsequent studies could overcome as yield data becomes more available. The numerical analysis in this thesis utilizes the county-level yield data due to the lack of farm-level yield data. Thus, since the county yield data are available, conducting research on area-based insurance may provide more valuable analysis to develop a better crop insurance for Indonesian farmers. Moreover, collecting seasonal rice yield data is imperative to calculate a more accurate premium rate since the yield variation in each planting season is dissimilar.

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