Farms, Farmers and Farming:
a Perspective through Data and Behavioral Insights†

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Abstract

This paper aims to improve our understanding on Thai agriculture, the sector that currently employs about 30% of the country's labor force. We draw out key stylized facts on our farms, farmers and farming from various granular data sets that allow us to observe what has happened at the plot, labor and household levels over the past decade, and cover more than 90% of farmers nationwide. We then use lab in the field experiments to understand behavioral insights that underly farmer's decision making and incentives, and hence their roles in improving effectiveness of agricultural policy and extension. Our results shed some lights on the key challenges and opportunities for Thai agriculture, which could provide implications on how to design, prioritize and implement policies to ensure that our farmers stay competitive, resilient and sustainable.

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Introduction

Agriculture has been one of the importance backbones in Thai economy, despite its low and slower growth relative to other economic sectors. With the stable occupation of approximately 40% to the country's total land area, the contributions of agriculture to the labor and gross domestic product (GDP) have been diminished over the past three decades accounting for 30% of total labor force and 10% of GDP in 2018 as illustrated in Figures 1a, 1b, and 1c, respectively. The agricultural sector also has generated the lowest value added per worker with the slowest growth relative to other economic sectors (Figure 1d).

Figure 1 here

For the international perspective, Thai agriculture has similar structural transformation patterns relative to other countries, but it has relatively low and slower growth in value added per worker. According to the World Bank Development indicators, Thai agriculture has similar patterns of the changes in the percent utilization of agricultural land, the percent of agricultural labor to total labor, and the percent of agricultural value added to GDP since 1990 relative to the leading agricultural producers (i.e., the United States: USA, Australia: AUS, the Netherlands: NLD, China: CHN, and India: IND) and the neighboring countries (i.e., Vietnam: VNM, the Philippines: PHL, Cambodia: KHM, Laos: LAO, and Myanmar: MMR) as shown in Figure 2a, 2b, and 2c, respectively. However, the contribution of agricultural labor to total labor is three times higher than that of the contribution of agricultural value added to GDP unlike the leading agricultural producers such as United States, Australia, and the Netherlands. As a result, the Thai agricultural value added per worker has slower growth and is a lot lower than the agricultural value added per worker of other leading countries (Figure 2d).

Figure 2 here

What drive Thailand's agricultural growth over the past 60 years? The increasing role of the improvement in the total factor productivity (TFP) is the answer, but the agricultural value-added and TFP growth of Thai agriculture have been slow down with low growth rate relative to neighboring countries and leading global agricultural producers. Using the estimated total factor productivity (TFP) data provided by the USDA Economic Research Service, the Thai agricultural growth was mainly driven by the expansion of agricultural land during 1961-1990, while it was mainly escalated by the improvement in the TFP after 1990 as demonstrated in the upper part of Figure 3. Since 1981, the agricultural value-added growth was diminishing over time with the lower growth rate compared to the leading agricultural producers and neighboring countries, and the negative agricultural value-added growth rate was revealed during 2011-2016 as shown in the middle part of Figure 3. Moreover, the TFP in Thai agriculture has grown at the low rate compared to leading agricultural producers as presented in the lower part of Figure 3. Figure 4 plots export share in the world market of our key crops and shows the potential declines in some key crops. Are we looking our competitiveness in the world market?

Figure 3, 4 here

What happen to Thai agriculture? This paper provides landscape knowledge of the development of Thai agriculture through various granular data and behavioral insights. The objective is to draw out key challenges, opportunities and policy priorities for improving competitiveness and sustainability of Thai farmers and Thai agriculture in general.

The paper has four sections. Section 1 draws out key stylized facts on the dynamics of farms, farmers and farming practices. These stylized facts then form a list of key challenges (both from structural problems and external forces) and opportunities for Thai agriculture. Section 2 brings all the stylized facts together and uses the stochastic frontier analysis to identify and prioritize the key drivers to (increasing and decreasing) household's agricultural productivity and competitiveness, and how the mechanisms vary across farms, farmers and farming practices. We then use the estimated results to project the potential effects of various challenges and opportunities identified earlier on agricultural productivity and the geographical variations of these effects. These results thus could imply how to prioritize policies to enhance agricultural productivity and competitiveness.

As we identify that technology and innovations have been one of the important sources for farmer's productivity growth, Section 3 attempts to provide understanding of the current stage of technology development and adoption in Thai agriculture. We use meta analysis to synthesize findings from the growing stock of existing research studies in Thailand over the past decade available from the Thailand Research Fund and the National Research Council of Thailand, and consider the landscape of technology in the rice value chain as a case study.

How do we put the policy priorities identified in Section 2 into practice and how do we get smallholder farmers to benefit from technology in Section 3? Section 4 then shifts gear and explore the role of behavioral insights in improving the effectiveness of agricultural policy. We consider policy priority to enhance smallholder farmer's technology adoption as a case study. We use lab in the field experiments conducted on around 400 farmers in Phatumtani and Kalasin to understand farmer's behavioral biases and their effects on farmers' incentives and learning, and on the effectiveness of agricultural extension and policy implementation. This section ends with a discussion that relates our findings from this field experiments to those of existing research project that use randomized control experiments to test the effectiveness of various incentive linked policy designs. Finally, we draw out some key takeaways of the paper with implications on how to design, prioritize and implement policies to ensure that Thai farmers stay competitive, resilient and sustainable.

1. Stylized facts on farms, farmers and farming

This section draws out key stylized facts on our farms, famers and farming and reveals seven major problems and two key opportunities of Thai agriculture. The results draw extensively from Attavanich et al. (2019).

1.1 Data

Our analysis relies on five main sets of granular data including: (1) Farmer registration (2015-2017) from the Department of Agricultural Extension (DOAE) covering 5.8 million households, 15.6 million labors and 12.8 million plots or almost 90% of farmers in Thailand in 2017; (2) Agricultural census (2003, 2013) collected by the National Statistical Office (NSO) covering 5.9 million households, 19.6 million labors and 10.7 million plots in 2013 or almost everyone; (3) Agricultural household socio-economic and labor survey (2006-2017) collected annually from national representative samples by the Office of Agricultural Economics (OAE); (4) Policy participation administrative data from the DOAE covering every rice farmer who participated in government policies and assistance in 2018 and the data also allow us to link every policy that each farmer participate; and (5) District-level agricultural productivity for key crops and monthly prices collected by OAE. Table 1 summarizes these data we used.

Table 1 here

1.2 What happen to Thai farms?

1.2.1 Farm size

Majority of farmers are smallholders. Our study found that the majority of Thai farmers are smallholders holding a small amount of land and the size of farmland has continued to decrease over time. When considering the cumulative distribution of farmland for households in 2017 (Figure 5a), we discovered that 50% of Thai farm households hold farmland less than 10 rais and approximately 20% of Thai farm households hold farmland greater than 20 rais. Comparing between 2003 and 2017, the size of farmland continuously declined in every group of farmers.[1] Moreover, in 2017, Thai farm households had an average of 14.3 rais of land holding. Figure 5b shows that most households holding farm size of 40 rais or more were in the Central and lower section of the Northern regions. Comparing farm size among countries, we found that farm size in Thailand is still larger than that in other developing countries in Asia such as Vietnam, Indonesia, Cambodia, and India, which had the average farm size of 3.9, 5.8, 8.2, and 8.3 rais, respectively, but it is lower than that in leading global agricultural producers such as the Netherland, Brazil, the United States, and Australia, which had the average farm size of 138, 455, 1,115 and 20,270 rais, respectively (FAO 2015; Lowder et al. 2016).

Figure 5 here

1.2.2 Land ownership

Problem 1: Still large inequality in land ownership and some 40% of farmers still did not have full land ownership. The analysis revealed that some 40% of farm households did not have land ownership and only 42% of them can access to water resource creating the large inequality of accessing to land and water resources. There are four categories of farmland holdings at the household level which are: 1) Full ownership such as land types with a tile deed and a certificate of utilization (NS5 or NS.3K); 2) Other types of ownership which may have restrictions on sales or transfers such as a certificate

[1] We note however that the difference in farm size distribution between in 2017 and those in 2003/2013 could have been due to differences in data sources, where the former is from farmer registration and the latter from the census. Farmers tend to have incentive to report and break out their farm size in the farmer registration so that they can maximize their eligibility to government programs, which tend to peg with farm size.

of agricultural land reform; 3) Rent land; and 4) Land without a document identified rights. From Figure 6a, only an average of 60% of agricultural households fully owned their lands. Most of which were in the Northeast and the Southern regions and they also had high proportions in other types of ownership. While households renting farmland had high proportions in the Central and the lower Northern regions, households without land ownership scattered in all regions especially in highlands and forests.

Figure 6 here

1.2.3 Access to water resource

Problem 2: Almost half of farmers still did not have access of water resource and two third still do have access to irrigation. For the perspective of access to the water resource, Figure 6b shows that in 2017 only 42% of the agricultural households could access to water resource, which is the most important among agricultural assets. Most of which were in Bangkok and its vicinity. When considering the type of water sources, we found that only 26% of the agricultural households could access to irrigation system and most of them were concentrated in the Central, the lower North, and Bangkok and its vicinity. The data also revealed that 11% of the households built and used their own water sources, with high proportions in the Northern and Northeastern regions, and 6% of the households used natural and public water sources, with high proportions in the Northern region. Overall, access to water resource of agricultural households is limited in the lower Northeastern and the Southern regions compared to other regions.

1.2.4 Climate risk and climate change

Problem 3: Increasing frequency and intensity of disasters and potential impacts from climate change. Agriculture is potentially the most sensitive economic sector to increasing frequency and intensity of disasters, and climate change and climate change is expected to generate tremendous damage values to Thai agriculture. Studies confirmed that climate change already created the loss to the agricultural sector of many countries around that world and the damage value will be increased in the future especially in developing countries (e.g., Mendelsohn et al. 1994; Attavanich and McCarl 2014; Brown et al. 2017). According to the DOAE statistics reported during 2006-2018, disaster affected agricultural areas from floods and droughts in Thailand have increased overtime with higher intensity (Figure 7a). A majority of affected areas were from the Northeastern region. We note that the statistics reported by DOAE usually tends to undervalue the actual economic loss because the affected areas must be completely damage in order to obtain the relief claim program. Using the Ricardian analysis, Attavanich (2017) estimated that climate change is projected to generate the accumulated total damage of 0.61-2.85 Trillion Baht, or average damage of 17.91-83.83 Thousand Million Baht annually during the 2011-2045 period to Thai agriculture. The rainfed farms will adversely be affected by climate change more than the irrigated farms. At the provincial level, the study revealed that the Southern region is projected to be negatively affected the most followed by Eastern region, and Central region, respectively. Surat Thani's agricultural sector will receive the highest average annual negative impacts from climate change of 2,260-7,538 Million Baht). Nakhon Si Thammarat (1,339-4,736 Million Baht) ranks second followed by Chumphon (1,270-4,580 Million Baht), Songkhla (1,248-4,136 Million Baht), Nakhon Ratchasima (661-3,945 Million Baht), respectively.

Figure 7 here

1.3 What happen to Thai farmers?

1.3.1 Demography

Problem 4: Our farmers are rapidly aging and almost 40% of farming households have old labor working on the farm. The Thai agricultural sector is facing an aging problem which is faster than the aging situation of the country and its severity is different across regions. Figure 8 shows that the proportion of aged labors (over 60 years) increased from 13% in 2003 to 19% in 2013, which is higher than the country's proportion of aged labors (14%) reported in 2017. Conversely, we also found that a proportion of young labors (15-40 years) decreased significantly from 48% to 32% in the same period.

The aging problem has been largely prevalent and intensified within farm households. Using the social economic and agricultural labor survey in the past 10 years from the Office of Agricultural Economics to fulfill the Agricultural Census conducted in 2003 and 2013, we found changes in proportion of elderly labors and the average age of household heads over the past 10 years as illustrated in Figure 9a. The data showed that the proportion of elderly labors was likely to increase continuously from 36% in 2008 to 46% in 2018 as well as the average age of the household head, which increased from 54 years old in 2008 to 58 years old in 2018. The severity of entry to the aging society of Thai agricultural households is different across regions. From Figure 9b, many areas in the

Central region and suburbs have higher proportions of elderly labors in households than in other regions of the country. We can also see that the average age of household head was high in many provinces of the Central, Northeastern, and Northern regions. Top seven provinces with the oldest head of households were Samut Songkhram, Sing Buri, Nakhon Nayok, Ang Thong, Roi Et, Mahasarakham, and Khon Kaen (Figure 9c).

Figure 9 here

1.3.2 Education

Opportunity 1: Increasing education especially among young labors. The education level of Thai farmers has been improved especially the group of young farmers. Figure 10 shows the proportions of agricultural labors who graduated at least upper secondary school, which increased from 12.1% in 2003 to 21.5% in 2013. This finding could provide an excellent opportunity of introducing modern technology to improve the productivity of Thai farming.

Figure 10 here

1.4 What happen to Thai farming?

1.4.1 Structural transformation

The structural transformation of Thai agriculture has been changing by increasing use of mechanization and decreasing use of labor. Unlike the use of labor per rai of Thai agricultural households, which decreased in almost all areas, numbers of households using mechanical equipment have significantly increased. Since 2003-2013, Figure 11 can clearly reflect the structural transformation of Thai agricultural sector, which is in accordance with many developing countries (Bustos et al. 2016, FAO 2015). Ratio of household labors who primarily do agriculture decreased the most in all areas, while ratios of households using machinery increased in all areas especially in the Northeastern, Northern, and Southern regions of the country. However, more than a half of such increase in the Northeastern and the Northern regions came from the increasing proportion of households using traditional machinery. In addition, the use of modern machinery, measured by the ratio of households using modern machinery to total households using either traditional or modern machinery, was highly concentrated in the Central and lower section of the Northern regions as shown in the right-hand side of

Figure 11, and at the national level the ratio of households using modern machine to total households was equal to 0.60 in 2013.[2]

Figure 11 here

Large variations in the use of modern technology were still detected by several characteristics such as farm size and agricultural activities. Considering the farm size, the data from 2013 Agricultural Census revealed clearly that the ratio of small-farm households using modern machine to total small-farm households was less than that of medium-farm and large-farm households using modern machine accounting for 0.4755, 0.6708, and 0.7591, respectively (Maps with green color in Figure 12). The use of modern machine also varied by agricultural activities with the highest ratio of households using modern machine from growing sugarcane (0.8172) followed by maize (0.7480), cassava (0.7468), rice (0.7208), rubber (0.6081), oil palm (0.5800), perennial crops excluding oil palm and rubber (0.5772), vegetable (0.5606), and milk cow (0.5133), respectively (Maps with blue color in Figure 12).

Figure 12 here

1.4.2 Farming patterns and dynamics

Opportunity 2: The potential gains from economies of scale due to geographically concentrated agricultural production. Figure 13 shows the concentration of each agricultural activity such as dark green spot indicating the area of rice farming which are concentrated in the provinces of the Chao Phraya river basin and the Northeastern region, and pink dots represent the rubber plantation areas that are concentrated in many provinces in the Southern region. Overall, Thai agriculture is more diverse. Comparing from 2017 Farmer Registration and 2013 Agricultural Census at the provincial level (the middle part of Figure 13), we found that the proportions of agricultural areas throughout the country have increased various agricultural activities. Considering the use of the modern machinery proxied by the use of tractors (Right side of Figure 13), we found that the households renting machineries were spatial concentrated which may be beneficial in terms of management, and transportation cost reduction. The proportions of

[2] In the agricultural census, there are 21 types of agricultural household machinery usage ranging from soil preparation, cultivation, harvesting, and processing agricultural products. This study has defined a traditional machine as a labor-intensive machine that can perform only one function such as a walking tractor, a manual pesticide sprayer, a manual weeding machine, a manual planting machine, and a threshing machine. While a modern machinery is a capital-intensive machine that can perform more than one function such as a tractor, a motorized pesticide sprayer, a motorized weeding machine, an automatic planter, a combine harvester etc.

such households have increased unlike the proportions of the households who owned or used tractors from other sources which have decreased in almost all areas. Economies of scale in Thai agricultural sector that facilitates the current agricultural machinery rental market, therefore, may be an important mechanism to unlock cost issues which makes small-scale farmers more accessible to technology. This finding is in line with Siamwalla and Poapongsakorn (2017) who reflected this fact through the development of Thai rice production process.

Figure 13 here

Considering the household's farming portfolio, our study revealed that two third of households still grow one crop a year, especially for key economic crops. Figure 14a shows the important characteristics of agricultural activities for crop rotation such as corn planting after rice and/or glutinous rice harvesting which is mostly found in the Northern region, and alternating between rice and glutinous rice which is normally found in the Northeastern region. Although the irrigation area in the Central region can do agriculture throughout the year, most agricultural households grow monoculture, especially the planting of in-season rice and off-season rice accounting for 88% of the households that are engaged in a rotation of monoculture.

In addition to the crop rotation activities, we explored the diversification of farm activities of households in 2017 shown in Figure 14b. Generally, there are farmers who, in addition to growing rice, also grow 1-2 other main crops. The top seven most common characteristics, which cover half of the farmers who did not do monoculture, consist of: 1) rice and glutinous rice 27%; 2) rice and cassava 6.1%; 3) glutinous rice and rubber 4.5%; 4) glutinous rice and sugarcane 3.4%; 5) rice and rubber 3.4%; 6) glutinous rice and cassava 3.1%; and 7) glutinous rice and corn 2.8%. The spatial differences in agricultural practices of households from Figures 14b and 14c consist of: (1) rice and glutinous rice, most found in the upper Northeastern region; 2) rice and cassava in the Central region; 3) glutinous rice and corn in Northern region; and 4) palm oil and rubber in the Southern region. Figure 14d shows that the proportion of households undertaking the organic and New Theory farming have not reached 0.25%. Even provinces with pilot projects such as Kalasin, Nakhon Ratchasima, Ratchaburi, Nakhon Sawan etc. still have the proportion of households undertaking the New Theory farming lower than the average.

Figure 14 here

Majority of households still stick with "high risk low return." Integrated agriculture can increase risk-adjusted returns. Examining the results of each type of integrated agriculture including monoculture, we found that many forms of integrated agriculture provide higher risk-adjusted returns than the monoculture does (Left-hand side of Figure 15). So, if agricultural households growing monoculture (especially sugarcane, corn, glutinous rice, rice and oil palm) diversify their farming practice by dividing their farmland to cultivate other major crops, their risk-adjusted return will be increased. According to our estimation, growing monoculture provided high risk-adjusted returns for the main crop activities such as rubber. Although diversifying agriculture may provide similar risk-adjusted return, farmers can use the integrated agriculture as an alternative to adjust their risk levels as needed.

When considering only the households that grew rice as an example, diversified agriculture yielded higher risk-adjusted return than growing only rice in almost every area. The right-hand side of Figure 15 shows different choices of farmers throughout the country. It was found that 92% of all provinces who grew rice along with other major crops had higher risk-adjusted returns than growing only rice. Moreover, from 60% of the provinces, rice monoculture is an alternative method that provides the lowest risk-adjusted returns. Comparing the return per a standard deviation, we found that the households that grew only rice received 0.34% of their returns, while other options such as growing rice and sugarcane and growing rice and corn gave higher return at 0.58% in both options.

Figure 15 here

1.4.3 Productivity

Problem 5: Low and large variations in productivity and productivity growth. Using the data from the Office of Agricultural Economics, we found that yields per rai of in-season and off-season rice were 461 and 573 kilograms per rai in 2018, which was lower than other countries such as Vietnam, the United States, and China whose yields were 900, 880, and 1,080 kilograms per rai, respectively (FAO Stat 2017). The high variation of rice yields is also extremely high. Low and large variations of yields also found in maize, cassava, natural rubber, and oil palm as illustrated in Figure 16a. Considering the average annual growth rate during 2012-2017 shown in Figure 16b, we discovered that the variation of average annual growth rates of selected key crops is also high ranging from negative to positive growth rate corresponding to their yields. Figure 16c shows geographical variations in growth of crop yields across the country during 2012-2018. Large variations ranging from negative to positive productivity growth of all selected key crops are revealed in many areas across the country. While we observed the prevalence of negative growth rates (less than 10 percent) of in-season and off-season rice, cassava, and natural rubber in several areas of the country, a majority of areas growing maize and oil palm experienced positive productivity growth rates during 2012-2018. Several new areas growing oil palm in the Northern, Northeastern and Central regions experienced doubled-digit growth of yield.

Figure 16 here

1.4.4 Profit-cost structure

Problem 6: Increasing production costs along with increasing fluctuation in revenue and value added have been squeezing farmer's net income. Part of which is due to the market structure of input and output, which tend to be less competitive with long supply chain. According to the statistics provided by the Office of Agricultural Economics, the production cost of selected key crops has been increasing over the past decade. Costs of labor, fertilizer, and land rent have the largest contribution in total cost of production. Unlike other crops, cost of seed has the largest share to total cost of production in oil palm. Among selected key crops, farmers growing in-season rice, sugarcane and natural rubber suffered the most since 2013 as a result of the negative net farm income. Although the situation of farmers growing maize, cassava, and oil palm was better than that of farmers growing in-season rice, sugarcane and natural rubber, the net farm income of these crops has been squeezing overtime. As a result, fragility of the net farm income may possibly a key factor leading to the agricultural household debt.

Figure 17 here

1.5 Markets

Stickiness between export price and farmgate price are found in all selected key crops reflecting the high degree of domestic buyers' monopoly power and high degree of price intervention policies. Comparing the price transmission between the export price and farmgate price from 2009 to 2018, we observed that, for rice, paddy rice had the gap between export and farmgate prices larger than the Jasmin rice as shown in Figure 18a. In some years, the export prices of these two rice types changed in the opposite direct to their farmgate prices. When the export prices increased, the farmgate prices usually increased at the rate lower than the changes in export prices. These evidences reflect the high degree of domestic buyers' monopoly power in the rice markets. This conclusion can be extended to the markets of maize, rubber, and oil palm. Besides the monopoly problem, the domestic price intervention policy is also a key factor that obstruct the price transmission between export and farmgate prices. The clear evidence, for example, can be observed in the rice markets from the rice-pledging program during 2011-2013.

Degree of buyers' monopoly power varied spatially across locations captured by the correlation coefficients between export and spatial farm gate prices, the ratio of miller's capacity to rice production, and distance from farm plot to miller. By calculating the correlation coefficients between export and farm gate prices of Jasmin and paddy rice, our study discovered the high correlation coefficients between two rice prices reflecting the high degree of competition in the almost all provinces in Bangkok's vicinities, Central regions, the lower section of the Northern region. Among provinces in the country, provinces in the Northeastern region have the lowest correlation coefficients between export and farm gate prices echoing the high degree of local buyers' monopoly power. The left-hand side of Figure 18b illustrated our findings. When mapping the location and capacity of rice millers (Second left of Figure 18b) with the rice production and shortest distance from the plot to miller to observe the degree of competition in the local rice markets, our study found that the Central region has the highest ratio of miller capacity to rice production compared to other regions as shown in the second right of Figure 18c. Moreover, we found that the rice millers in almost all regions generally locates in the areas closed to the farm plots excepting for the mountainous areas in the Northern and the upper section of the Northeastern regions and areas in the lowest part of the Southern region.

Figure 18 here

1.6 Household debt

Problem 7: Rising household debt and debt accumulation of farmers especially due to the nature of agricultural production and government policies. Using data of BAAC loan portfolio of sampled households from the 1st quarter of 2014 to the 1st quarter of 2018, our study revealed that farm household debt and its accumulation have been increasing overtime. By decomposing the farm household debt, we found that debt generated from buying working capital in agriculture has the largest share among sources of debt followed by debt generated from investment in agriculture and debt generated from memorandum and restructuring, respectively (Figure 19a left-hand side axis). The delinquency rate was about 3 percent over the study period and has been increased since the 1st quarter of 2016 (Figure 19a right-hand side axis). Considering the new debt creation from government policies during the 1st quarter of 2015 to the 1st quarter of 2018, we found that a majority of new debt from policies was created from other policies such as the programs aiming to replace off-season rice to maize, credit card for farmers and providing loan with very low interest rate. Debt restructuring policy also a factor causing the creation of new debt (Figure 19b left-hand side axis). Figure 19b on the left-hand side axis also shows that approximately 30 percent of farm households received the assistance from these policies.

By composing the farmer's outstanding debt classified by age, we revealed that the mean debt outstanding per household had the inverted U-shape relationship with the age of farmer (Figure 19c). It started to increase from the age of 25 years old and then reached the highest level at the age of 47 years old. Then, the debt per household tends to decline after the age of 47 years old. Debt created from purchasing working capital in agriculture contributed the largest share among other sources of debt. By focusing on the new debt creation from policies classified by age shown in Figure 19d, we found that the largest source of debt created from policies was from the debt memorandum program. The new debt created from debt restructuring program tends to escalate as the age of farm household increases.

Figure 19 here

1.7 Policies

Problem 8: existing agricultural policies tend to put more focus on short-term assistances and could unintentionally create bad consequences especially in disincentivizing farmer's adaptation and inducing risk taking. Using the participation data provided by the Department of Agricultural Extension and the social network analysis, we explore the linkages of farm households obtaining government policies and assistance. Among government policies and assistance provide, Figure 20a revealed that the compensation for harvesting expenses was provided to the largest group of farm households accounting for 95% of total farm households followed by insurance for the in-season rice (44%) and debt memorandum (36%), respectively. We also observed that one farm household obtained the support from several policies and assistance. For example, a farm household obtaining the compensation for harvesting expenses also received the support from programs related to insurance for the in-season rice, debt memorandum, disaster relief, organic farming, growing other crops after harvesting the in-season rice, big-farm program, and credit assistance from disaster. Figure 19b demonstrates the combination of policies and total policy assistance received by a household by farm size. Our study revealed that a majority of farm household obtained only the harvesting support, the combination of support from harvesting, insurance and debt memorandum. Households having the small farm size tend to receive the largest portion of assistance from harvesting support. As farm size increases, the share of households obtaining the harvesting support tends to decline and oppositely the share of households obtaining the combination of support from harvesting, insurance and debt memorandum, and the combination of support from harvesting, insurance, debt memorandum and relief tends to increase. The mean assistance received by a household ranges from about 12,000-20,000 Baht. The mean assistance is positively related to the farm size.

Figure 20 here

1.7 Takeaways: Key challenges and opportunities for Thai agriculture

In sum, our paper has identified seven challenges, majority of which are structural problems in Thai agriculture.

First, some 40% of Thai farmers still did not have land ownership and majority of our farmers are smallholders. In the latest work, Attavanich et al. (2019) found that land ownership has been one of the key factors to enhance farmer's adaptation and adoption of alternative, high-valued crops and diversification. Literatures also found that land ownership significantly affects farmer's incentive to invest in productivity enhancing land improvement. Attavanich et al. (2019) further found that farm size positively affects the use of modern mechanization and productivity, potentially through economies of scale.

Second, almost half of farmers still did not have access of water resource and two third still do have access to irrigation, of which Attavanich et al. (2019) shows significantly affect productivity and farmer's adaptation.

Third, Thai farmers face increasing frequency and intensity of disasters and high potential impacts from climate change. Literatures show that shocks and risks not only create impediment to farmer's income and vulnerability, but also constrain their incentive to invest and adapt to enhance productivity.

Forth, our farmers are rapidly aging and almost 40% of our farming households have old labor working on farm. Attavanich e al. (2019) further found that technology adoption and productivity decline significantly in the households with older head and larger proportion of old labor.

Fifth, household's agricultural productivity has been low with slow growth. And part of which is due to the fact that majority of households still stick with "high risk low return" monocropping. Relaxing constraints to productivity improvement would be very critical and would involve both enhancing the use of technology among farmers as well as relaxing impediments on farmer's incentive to adapt.

Sixth, the increasing production costs along with increasing fluctuation in revenue and value added have been squeezing farmer's net income. Part of which is due to the market structure of input and output, which tend to be less competitive with long supply chain.

Seven, rising household debt and debt accumulation of farmers especially due to the nature of agricultural production and government policies. Entering of Thai agriculture to aging society and shocks from changing climate and its variability could create risk to the financial system especially BAAC, the major loan provider. Previous studies also revealed that increasing debt in low productivity farms creates the poverty trap to farm households.

Eight, existing agricultural policies tend to put more focus on short-term assistances and could unintentionally create bad consequences especially in disincentivizing farmer's adaptation and inducing risk taking. Literature also found that many policies that distort market mechanism could further destroy the market functioning.

We further identify at least two opportunities for Thai agriculture. First, we found that education level of agricultural labor has been increasing especially among young labors. And this could potentially enable learning and adoption of technology and innovation. And second, we found that agricultural production has been geographically concentrated. This could open up opportunities gain from the economies of scale. And one example we found is the emergence of and rising rental market for mechanization, which could unlock access to modern machines especially among the smallholders, who would otherwise not have been able to acquire due to high cost.

The next section attempts to prioritize these challenges and opportunities by identifying the contribution of these factors to productivity (de) growth.

2. Understanding drivers to agriculture productivity and competitiveness

Integrating all of major problems and opportunities of Thai agriculture: What are the key sources of household's productivity growth? This section identifies key contribution to productivity growth and uses the estimated results to project the potential impact on productivity growth (and the geographical variations of these impacts) from the above challenges and opportunities.

2.1 Stochastic frontier analysis (SFA)

In order to understand Thai households' productivity, this study employs stochastic frontier analysis to exploit its advantage on micro-level data analytics over other frameworks. In addition, it also imposes a functional form and econometric techniques in estimating production function (Suphannachart and Warr, 2010) which is easier in interpreting results. Lastly, SFA allows farmers for attaining inefficient production which accommodates the model to be able to observe dispersed competitiveness in various to farmers' characteristics.

The model

The model is structured on a Cobb-Douglas production function where productivity, denoted as ε_{it}, can be estimated. Furthermore, the richness of micro-level data allows the model to embed land, a crucial input in agricultural production as suggested by USDA's study (Fuglie, 2015), in addition to the traditional inputs of capital, labor and material. This can be expressed as YAKLM model (Seker and Saliola, 2018) which can be shown as:

$$Y_{it} = \beta_0 K_{it}^{\beta_1} L_{it}^{\beta_2} M_{it}^{\beta_3} Lnd_{it}^{\beta_4} \varepsilon_{it} \quad (1)$$

According to model in equation (1), the deviations (ε_{it}) of household i at time t can be composed of v_{it} and u_{it} in equation (2). While both v_{it} and u_{it} are independently and identically distributed (IID), v_{it} and u_{it} are different. In contrast to v_{it} that has a two sided or symmetric distribution, u_{it} has a one-sided distribution.

$$\varepsilon_{it} = v_{it} - u_{it} \quad (2)$$

In this approach, the error term u_{it} is restricted to be positive which is useful to measure inefficiency (StataCorp, 2003). After estimating u_{it} from equation (1), we simultaneously regress from the inefficiency model in equation (3) by using u_{it} as a dependent variable, to understand farmers' productivity.

$$u_{it} = \delta_0 + \sum_{n=1}^{N} \delta_n z_{nit} + w_{it} \tag{3}$$

z_{nit} includes all identified variables to represent key economic issues such as aging, climate, market, policy and technology from the previous section.

Finally, we can estimate technical efficiency (TE) of each farmer i at time t by using equation (4) by comparing rescaled u_{it} with the frontier that we attained from equation (1). Thus, the value of TE will be ranged between 0 to 100%.

$$TE_{it} = \exp(-\hat{u}_{it}) \tag{4}$$

Estimated results

In the first stage, Thai households' production tend to be land intensive since land's factor share, which can be described by the coefficient of land, is the largest among all factors. During 2006 – 2016, a 1% increase in agricultural land can raise 0.43% of output while a 1% increase of material, labor and capital inputs can raise 0.39%, 0.12% and 0.10% of outputs, respectively. The result seems to be similar with other studies using micro-level data. For example, households in the U.S. do not depend much on labor and capital inputs in order to increase outputs. (Wang et al., 2017) However, the result is different from other previous studies in Thailand, especially the results which are based on macro-level data (Suphannachart and Warr, 2011) due to the difference in data definition. For example, in some studies that use macro-level data, households' capital variable also includes public capital such as infrastructure, R&D, and etc.

The first stage also tests whether the Thai farming has the production frontier or not. Table 2 shows that an existence of production frontier in this model is statistically significant. Since the likelihood ratio is larger than the critical value, we can reject the null hypothesis that u_{it} is zero or there is no frontier. Thus, we can use this model to estimate technical efficiency of each farmers during 2006 – 2016 in the next step.

Table 2 here

In the second stage, we find that key economic factors have statistically significant in determining inefficiency where production is deviated from the frontier. Firstly, aged farmers are negatively correlated to efficient farming as expected and in line with the results of Chantarat et.al. (2019). Secondly, climate shock both from rainfall and temperature which directly affect growing patterns of plants can lead to less efficient farming because Thai households' farming is well immune to such shocks. Thirdly, income subsidy can worsen farming efficiency as it discourages farmers to adapt in order to enhance immunity and productivity. For example, Thai farmers wouldn't bring extra income from rice-pledging programme to invest and enhance their productivity. (Attavanich, 2016)

However, if farmers employ modern machines and equipment such as tractors, etc., their farming can be drawn toward the frontier which means more efficient farming. Moreover, this study also finds other external factors including the level of normalized rainfall (Oury index) and irrigated farm, which is positively correlated to production efficiency.

In the final stage, Figure 21 shows the estimated technical efficiency of sampling households, which is on average equal to 65.3% of the frontier in 2016. In addition, we find that size of farm matters because large farms are slightly more efficient than medium size farms. And, medium farms are more efficient than small farms as well.

Figure 21 here

2.2 Geographical variations of contribution to productivity

In this section, we project geographical variations of contribution to productivity by using variations in explanatory variables constructed from 2017 farmer registration data. Using the estimated coefficients in Table 2, we distinctly estimate the productivity effect of each explanatory variable by holding other variables constant. Two climate change scenarios (RCP4.5 and RCP8.5 from the Intergovernmental Panel on Climate Change (IPCC) (2013) are used to create projections of geographical variations of productivity effect from climate change during 2046-2055. RCP4.5 and RCP8.5 can capture the range of low and high impacts induced by climate change.

Our study found the largest negative effect on productivity from aging in the Northeastern and Northern regions, while the negative effect on productivity from high indebtness distributed equally across the locations. Productivity of farm households tends to increase in the irrigated areas mainly in the Central and the Northern regions. In addition, farms located in the Central region likely obtained the positive effect on productivity from modern technology (Figure 22a). Considering the climate change impact on productivity shown in Figure 22b, this study revealed that almost all farm households across the country are projected to encounter the negative effect from climate change. For the best case captured by RCP4.5, large projected losses of productivity are discovered in areas located in the lower section of the Northern region. The productivity loss is projected to increase in the higher degree of climate change capturing RCP8.5 (Worst case) as shown in Figure 23.

Figure 22,23 here

3. Technology as enables to agricultural productivity

3.1 Meta-analysis of technology landscape in the rice value chain

Population growth, climate change and other changes are the key driving forces for agriculture sector to find innovative solutions or technology to boost agricultural productivity, improve product quality and reduce the environmental impacts (Coca, 2017). Today, modern farms that adopted new and sophisticated technology operate differently from the past. Examples of advancement in technology used in agriculture sector are temperature and moisture sensors, robots, aerial images, GPS technology, etc. These advance technology allows agricultural production to be more efficient, safer, productive and environmental friendly. Benefits of agricultural technology include increasing crop productivity, decreasing the use of water, fertilizer and agricultural chemicals, reduced impact on natural ecosystem and less runoff of hazardous chemicals into rivers and groundwater. Moreover, robotic technologies enable more reliable monitoring and management of natural resources, such as air and water quality and gives producers greater control over plant and livestock production, processing, distribution, and storage, which consequently lead to higher efficiency and reduced environmental impacts.

This part of the study aims to provide an overview on the landscape of technology and the use of technology for agriculture throughout the agricultural value chain by conducting the meta-analysis. Meta-analysis allows researchers to synthesize the results of existing studies on the agricultural technology in Thailand context.

The main objective of this meta-analysis is to create understanding on the state of research and development of technology used in the agricultural value chain. The focus will be on rice and the rice value chain. The key questions to be answered from this meta-analysis are two-fold: (1) According to the existing research in Thailand on the development and introduction of technology related to rice, what are the currently existing technology at different part of the rice value chain. (2) What are the technology gaps in the rice value chain?

Conceptual framework

When conducting the meta-analysis under this study, one reviewed and synthesized the results from the existing studies at each node/part of the rice value chain. To be specific, one will highlight the landscape of technology currently exist at different part of the value chain, starting from resource utilization (land, water, soil etc.); production process; post-harvest management; rice processing, distribution and marketing. Figure 24 shows the conceptual framework used in this meta-analysis.

Figure 24 here

Methodology and data

This study will compile and review the reports related to technology in the rice value chain in the e-library of the Thailand Research Fund (TRF) as well as related studies in the database of the National Research Council of Thailand (NRCT). In addition, this study will also highlight the technologies used by private sectors and farmers in the rice value chain in Thailand. After reviewing the reports of past research projects funded by the Thailand Research Fund (TRF) in the e-library or online database of TRF, there are 25 studies that are directly related to the development or promotion of technology in the rice value chain. Under the National Research Council of Thailand (NRCT) database, there are 16 studies that are related to technologies in the rice value chain.

Landscape of Rice Technologies in Thailand from the TRF and NRCT databases

After reviewing the reports of past research projects funded by the Thailand Research Fund (TRF) in the e-library or online database, there are altogether 25 studies that are directly related to the development or promotion of technology in the rice value chain. In terms of positioning of technology in the rice value chain, we found that around 28 percent of these 25 studies focused on technology applied to inputs used in the rice production, such as rice varieties, fertilizer and nutrients, while around 16 percent of these studies focus on technology in the rice production process and quality control technology for rice outputs, i.e. during the milling process (Table 3). The results from the meta-analysis shows that around 12 percent of these studies highlighted the technology during harvesting and storage of rice as well as during the rice processing stage. There has been very limited research on the technology to enhance efficiency at the marketing stage for rice, such as packaging, etc.

Table 3 here

Table 2 provides a landscape of technology types used along the rice value chain under the TRF database. According to Table 4, a majority of studies focus on the rice processing technology (around 28 percent). Other technologies that are extensively researched include seed improvement technology, storage technology, insurance as the risk management technology and rice gene expression technology.

Table 4 here

Under the National Research Council of Thailand (NRCT) database, there are altogether 16 studies that are related to technologies in the rice value chain. Table 5 shows where these technologies fall in the rice value chain. As shown in the table, most of the research that were funded by NRCT (around 44 percent of these relevant studies) focus on the inputs component in the rice value chain, especially seed and rice gene. Around 25 percent of the studies related to technology in the rice value chain focuses on the production process and around 13 percent of these related studies focuses on the resource utilization, especially land use planning and water management. The rest of the studies touch on rice processing and marketing.

Table 5 here

Next, a summary by technology type is shown in Table 6. As shown in the table, out of 16 studies that look at the development or use of technology in the rice value chain, one finds that around 31 percent focus on seed improvement technology and 13 percent focuses on gene expression technology. The rest of the technologies include biotechnology; information technology; irrigation technology; land preparation, fertilizer management, planting and harvesting technologies; pest control technology; processing technology; rice planting technology; rice straw management technology and traceability technology.

Table 6 here

Figure 25 summarizes the names of technology in the rice value chain according to the research funded by the TRF and the NRCT online database.

Figure 25 here

One can notice that there has been quite limited research funded by the TRF on technologies that improve the utilization of land and water for rice production. There are technologies being proposed for land use planning and for management of irrigated water. The land use planning technologies include Geo-informatics technology to help in land use planning, the LANDSAT 5 TM and RADARSAT 1 database. For irrigated water management, the research proposed the use of "Tang" technique, which is the local irrigation water technology.

With regards to the inputs used in the rice production, including rice varieties or seed, fertilizer or nutrients, a number of technologies were developed. The technology related to the rice varieties or seed improvement include development of new aromatic rice varieties IR 77924-62-71-1-1-2 as well as the application of energy ion beam to induce mutation to jasmine rice (Oryza sativa indica KDML 105). Examples of other seed improvement technology include the peptide mass finger technique; SDS PAGE technique for protein extraction; soaking of rice seed in wood vinegar; the use of rice seed production technology; and the rice seed storage technology called seed priming. Technologies related to rice gene include DNA molecular mark, RARD mixture for DNA amplification, isolate 2 beta-glucosidase cDNA from germinating, DNA methyltransferase enzyme and gene in DNA methylation process. For technologies that are related to fertilizer and nutrient management, examples include the use of DSSAT and PDSS software for NPK fertilizer recommendation and SimRice software and green manuring.

At the rice production stage, technologies are developed and applied at different parts of the process, namely planting, nutrient management and weed control. For the rice planting stage, the machine transplanting technology was proved to give highest average yield per rai compared with other technologies, such as direct seeding and hand transplanting. In addition, with the application of this technology, the rice milling quality was excellent. Other rice production technologies include the use of Cupriavidus taiwanensis KKU2500-3 bacterium, the integrated pest management; the use of Antagonistic bactreria, endophytic fungi, plant extracts or natural substances, biological products, multilines, effective fungicides and integrated rice disease management; and rice terracing technology. For the nutrient management technology, micro nutrient, Iodine, Zinc and Iron were used to enhance the milling quality and the quality of the rice grain and flour products. For weed control, the research suggested to use a combination of mechanical control, chemical control and cloth dipped in glufosinate ammonium to apply onto the leaves of the weedy rice while they were at the panicle stage.

After the rice has been harvested, the storage technology becomes essential. Examples of proposed storage technology include the use of technology to reduce moisture content in rice and installation of ventilation system in the rice mill. Concerning the management of residues that resulted from rice production, the existing study proposed the use of rice straw management technology.

The technologies that are relevant at the milling and processing stage include stabilization of rice bran by heating and reduction of filtration time by vacuum filtration, modification of rice starch through the chemical and heat moisture treatments, and soaking of rice in water, reverse osmosis and calcium chloride solutions. To create value added for rice through processing, the existing study proposed the instant cooking rice technology.

At the marketing stage, technology for the milled rice was developed. Specifically, if the polyethylene bag is used, it is crucial that the milled rice be exposed to phosphine fumigation to eliminate infested insect. In addition, to maintain good rice quality, marketing management must be adopted so that the rice product will be quickly sold out (ideally within 4 months) and the package must be sealed under vacuum. Last but not least, the traceability technology was being proposed. The traceability system designed and implemented in compliance with the EPC global Network standard and XML based message enables the exchange of traceability data in the global traceability environment. Moreover, the use of radio frequency identification (RFID) for the identification of individual good package for verification of paddy identity has also been proposed.

Landscape of Rice Technologies in Thailand

When considering the technologies related to rice in Thailand, one found that the newly developed technologies mostly geared towards enhancing productivity and production efficiency, promoting efficient use of resources, minimizing the use of pesticide; reducing impacts on the environment as well as developing the rice varieties that are resistant to unsuitable environment. In addition to reviewing the papers under the TRF and NRCT databases, this section of the paper is devoted to show the landscape of rice technologies currently available in Thailand. Figure 26 contains a summary of the current state of technology used in the rice value chain (Tanprasert 2018)

Figure 26 here

According to Figure 3, at the resource utilization stage, i.e. land use planning, soil, and water, currently Thai farmers have been using the agri-informatics technology, such as Agri-Map or LDD Soil Guide app developed by the Land Development Department, Ministry of Agriculture and Cooperative, as well as other mobile applications developed by the private sector. For inputs used in the rice production, a number of technologies related to rice varieties are currently existing, such as the CRISPR-Cas and Cas protein, which help in promoting diversity in the rice varieties, as well as Marker Assisted Selection (MAS) and RiceFiT technologies which are used for selecting suitable rice varieties. During the rice production stage, many technologies are used by farmers; for examples, Plant Phenotyping Scanner, Biological fungicide "Howler", Smart sensor, FAARM Sense (smart monitoring technology) and FAARM FiT (smart controlling technology) as well as fertilizer management technology such as Bai-Khao App (Nitrogen estimator for rice field). The combined harvester has facilitated farmers during the harvest stage and the rice threshing machine and Grain Chilling technology are used during post-harvest and storage stages. In order to create value added in rice, technology has been used in processing of rice into new products, such as food (e.g. Energy gel, Rice Cider, rice jelly); medical supplies (e.g. gel pad); and cosmetics (e.g. hair serum, masking cream, lip balm). Last but not least, during the marketing stage, with the availability of social media and new technology, now rice products can be sold via the online platform, LINE, and Facebook. In addition, QR code is used to enable consumers to trace the origin of the rice products that they can be assured of the product quality.

The above evidence could reflect the potential opportunities in term of development of technology and innovation for Thai agriculture. The earlier section, however, show that the use of technology (proxied by modern mechanization as we do not have any data on technology use) still vary significantly across famers and areas. The next question we need to ask are what stimulate/constrain farmer's technological adoption and what should we do to promote the use of technology and innovation especially among our smallholder majority. The next section explore the role of behavioral insights in understand farmer's decision making and use the case of technology adoption to show how behavioral insights can improve effectiveness of agricultural extension and policies.

Behavioral insights to enhance agricultural competitiveness

4.1 Key behavioral biases of Thai farmers

Behavioral economics has shown us that decision making of human being might deviate a great deal from the rational decision predicted by traditional economic theory, which assumes that everyone has the same preference and utility that dictate optimal decision making. In reality, individuals have various behavioral biases that deviate their decisions away from rational one. And more importantly, variations in the degree of behavioral biases imply variations in 'optimal decision' across individuals.

Understanding individual's behavioral biases is critical and pre-requisite for understanding individual behavior and how they will response to various interventions. Our earlier results have shown some evidence that Thai farmers' decision and behavior (similar to those of farmers from the rest of the world) might have deviate from the rational/optimal ones, e.g., the evidence that majority of farmers still choose to do high risk, low return agricultural production, some groups still did not adopt technology, which could otherwise yield them welfare improvement, etc.

This section attempts to understand patterns of behavioral biases and how they vary across farm households using field survey and experiments conducted on around 250 farmers in Phatumtani and Kalasin in August 2019. In each province, we select 4 tambons with large proportion of rice farmers. Within each tambon we randomly select 5 villages. And in each village, we attempt to select sampled households with variations in age, gender land size and agricultural practices (with some farmers producing organic rice) in consultation with village heads. With some sample attrition, altogether, our sampled households are from 38 villages, 8 tambons in 2 provinces.

We asked a series of survey and experiment/game styled questions designed to elicit several aspects of behavioral biases (see appendix for our instrument)[3] known to affect farmers according to existing literatures. This section draws extensively from Chantarat et al. (2019).

[3] These are standard questions used in the behavioral economic literature to elicit behavioral biases.

What are key behavioral biases among Thai farmers?

Figure 27 displays distribution of 11 key behavioral biases that we have elicited from the field with each graph showing proportion of sampled farmers with different level of each behavioral bias. We also compare how these behavioral biases vary across groups, i.e., between low tech (those who still use primitive technology) and high tech (those who use modern technology) farmers and among farmers with different owned farm sizes. Among the key behavioral biases are

Risk aversion: Almost 35% of farmers have extreme degree of risk aversion and we find higher degree of risk aversion especially among the low tech farmers.

Loss aversion: Some 80% of Thai farmers express some degree of loss aversion. Literature shows that loss aversion when combined with risk aversion could reduce farmer's incentive to invest and adopt new farming practices and/or technology.

Present bias: We find that around 85% of Thai farmers have present bias to some degree and higher degree especially among the least wealthy group. Present bias has been shown in the current literature to have cause low level of saving and insurance.

Overconfidence: Around 25% of Thai farmers express high degree of overconfidence, which is known in some literature to have caused over indebtness.

Optimism: We found that around 60% of farmers are optimistic, which could have led them to overweight probability of gains and perhaps underweight probability of losses. Optimism has been shown in the literature to be correlated with low insurance uptake.

Status quo bias: About 55% of farmers expressed some degree of status quo bias, which could have caused them to accept the current condition, to stay where they are and to have no incentive to adapt their farming practices or adopt technology.

Self control problem: Interestingly almost 75% of farmers have some degree of self control problem. In the literature, self control problem has been one of the key causes of low saving and over-indebtness.

Social inherence: Around 40% of farmers have some degree of social inherence, which could have caused them to naturally follow social norm.

Trust: Thai farmers have high degree of trust but with varying degrees across entities. They trust family the most and business partners the least. Interestingly about 75% express some degree of trust on government.

Figure 27 here

How might these behavioral biases affect Thai farmers' decision making and their responses to extension and policies? Given the background knowledge of behavioral biases of Thai farmers, the next section explore how some of these biases could affect technology adoption.

4.2 Behavioral insights to enhance farmer's adoption of technology

Productivity growth in agriculture is one of the key sources of successful structural transformation and economic growth for poor countries (Gollin et al., 2002, Emerick et al., 2016 and De Janvry et al., 2016a). Yet, productivity growth in agriculture requires the availability of technological innovations for agriculture and adoption of these innovations by farmers. According to Kassie et al. (2011), adoption of agricultural technology has been associated with higher earnings and lower poverty. In fact, as pointed out by Ravallion and Chen (2004), the adoption of modern technology was among the driving forces behind the success of the green revolution.

However, a number of countries have a puzzling lag between the presumed availability of promising agricultural technologies and their adoption. Such phenomena have holding back the role of agriculture for development and hindering the agricultural productivity. A number of factors could hinder the adoption of new agricultural technology among smallholder farmers, such as time-inconsistent preferences, liquidity or credit constraint, information constraint, etc. (De Janvry et al., 2016b). In this paper, we argue that behavioral biases limit adoption of new agricultural technology by Thai farmers. We, therefore, conducted a lab-in-the-field experiment in two provinces in Thailand, namely Phatumtani and Kalasin provinces. Our objective is to test whether behavioral biases hinders the technology adoption and, by relaxing these constraints, will the uptake of agricultural technology among smallholder farmers be enhanced?

This section draws extensively from Mahasuweerachai et al. (2019). In this section, we capture liquidity constraint through the differential allocation of endowment, which is comprising of land, saving and debt. Farmers were assigned into low and high endowment groups. This constitutes the control group in our experiment. For the farmers in the treatment groups, they are subjected to two types of intervention, i.e. information diffusion enhancement through social learning and provision of subsidies. This paper examines the influence of information diffusion through learning from farmers to farmers on the adoption of a new technology. Specifically, we investigated whether farmers learn from others in deciding for oneself could be through the transmission of knowledge or of information about the behavior of others that can be imitated. The literature highlights that heterogeneity of conditions, such as soil types, skills, etc., may reduce learning from others in the social networks (De Janvry et al., 2016a). With more heterogeneity in the characteristics, learning from others could become limited and more private learning could be induced as farmers tend to learn more from farmers that are more similar to them than from the lead (best) farmers (Mobius and Rosenblat, 2014; Benyishay and Mobarak, 2018). This is also being tested in the experiment we conducted. If this is true, the smallholder farmers will be more convinced to adopt new technology by observing the decision of farmers who face similar challenges and conditions that are comparable to the conditions facing them. By addressing this issue, we could help us in shaping the policy recommendation on the type of lead farmers to be selected as promoters of new technology through the social learning process.

With regards to subsidies, since this type of policy is usually costly, difficult to target, prone to corruption and politically sensitive to remove once introduced, a number of studies were conducted to find the appropriate design of subsidies. The results from Carter et al. (2014) show that one-time subsidies to fertilizers and improved seeds effectively induced farmers' adoption in the short run and the demand persists over time and induced learning by others. In this paper, we looked at the influences of two types of one-time subsidies on technology adoption, namely cost of production subsidies and income subsidies.

In addition to the lab-in-the-field experiment, this paper also highlights the results from the field study conducted in Kalasin province by Mahasuweerachai et al. (2018) which attempted to use behavioral insights to enhance new agricultural technology adoption by smallholder farmers. The study was motivated by the low rate adoption of new crops under the Royal Initiative Foundation. The main barriers that hindered the adoption of new technology include farmers' inexperience that creates fear of loss (loss aversion). Mahasuweerachai et al. (2018) attempted to enhance the adoption of new crops by using the risk transfer mechanism, including the conditional loan to cover production costs at the beginning of the season and the payment of 5,000 Thai Baht per month over the 4 months during the off-season farming period. Such payment is in addition to the conditional loan and works as an advance realization of profits from the sales of new crops.

Such study examines whether the number of applicants for the new crop program increase after the risk transfer mechanism was implemented.

Review of related literature

There are a number of explanations for a limited or lack of adoption of agricultural technology. Examples of factors behind the failure to adopt new technology include (i) procrastination and time-inconsistent preferences (Duflo et al., 2011); (ii) high transaction costs due to poor infrastructure (Suri, 2011); (iii) lack of information and learning difficulties (Ashraf et al., 2009; Hanna et al., 2014); (iv) lack of agricultural technologies that are well suited to local conditions; (v) lack of formal insurance (Karlan et al., 2014); and (vi) insufficient asset endowments such as managerial skills to adopt new agricultural technology (De Janvry et al., 2016b). Figure 28 summarizes the key factors that could explain the lack of adoption of agricultural technology.

As shown in the figure, the key explanations are divided into 3 components, namely demand-side factors, mediating factors and supply-side factors. The demand-side factors are related to the farmers' asset endowments and behavioral traits. Lack of managerial skills can be one of the factors for lack adoption of modern technology. In addition, procrastination in putting money aside to invest in new farming practices is the factor that cause some farmers to run out of liquidity to devote for such investment.

Figure 28 here

Duflo et al. (2011) looked at the farmers' decision on fertilizer use in Kenya and found that, due to procrastination, there is the risk that all available liquidity will be gone by the time farmers have to apply fertilizer on their agricultural land. To deal with procrastination, Duflo et al. (2011) suggested that small, time-limited discounts on fertilizer could help induce sizable changes in fertilizer use. Their study also shows that heavy subsidies could induce fertilizer use by stochatically hyperbolic farmers, but they could lead to overuse of fertilizer by farmers who do not suffer from time-consistency problem. Thus, a "paternalistic libertarian" approach (Thaler and Sunstein, 2008) of small, time-limited discounts could yield higher welfare than heavy subsidies as this policy induce stochastically hyperbolic farmers to commit themselves to invest in fertilizer while avoiding distortion in fertilizer use among time-consistent farmers and the high fiscal costs associated with heavy subsidies.

The mediating factors are comprising institutional, markets and policy factors. Two main components of the institutional factors are credit and insurance. Smallholder farmers may face liquidity constraint, which prevents them from acquiring new agricultural technology. The study by Karlan et al. (2014) investigated this issue by conducting a natural field experiment in Ghana whereby rainfall insurance grant or cash grant were offered to maize farmers. The results of their experiment show that there were strong responses of agricultural investment to the rainfall insurance grant, but relatively small effects of the cash grants. When provided with insurance against the rainfall which is the primary catastrophic risk faced by the maize farmers, farmers are able to find resources to increase expenditure on their farms. This evidence shows that liquidity constraints are not as binding as typically thought but does not mean that there is absolutely no liquidity constraint since these farmers could still be constrained partially on the farm or in other domains of their life.

From the study of Emerick et al. (2016), the results of the experiment taken place in India show that, when superior agricultural technology such as flood-tolerant rice becomes available, the farmers increased the uptake of agricultural credit. The increase in the utilization of agricultural credit could be attributed to two reasons. First, utilization of credit could increase due to a demand effect where the increase in expected production in the future after adoption of new technology makes borrowing more desirable. Second, the increase in the credit uptake could be explained by the supply effect where credit constraints are a function of the borrower's expected production. There were several studies that used the randomized controlled trials (RCT) approach to identify the role of credit constraints and to find ways of relaxing these constraints. De Janvry et al. (2016b) provide examples of credit schemes for agriculture that could help relaxing the credit constraints include customization of repayment schedule to seasonality (Matsumoto et al., 2013; Beaman et al., 2015); availability of post-harvest loan to help farmers postpone the sale of their outputs to wait for a better price (Burke, 2014); flexible collateral arrangements such as stored crops with warehouse receipt; or providing lenders with more information about borrowers by using information from credit bureau.

Given that risk is among the major constraints on adoption of agricultural technology, there were some studies that focused on the role of index-based insurance as a tool for risk management for smallholder farmers. The studies by Cole et al. (2014), Cai (2016) and Elabed and Carter (2015) found that the index-based insurance is effective when used, but there is a problem of low uptake of this type of insurance. Belissa et al.

(2018) looked into the issue of liquidity constraint which prevents them from taking up the index-based insurance. They found that many smallholders in Ethiopia are unable to mobilize the resources needed to pay for payment of the insurance premium upfront when their disposable income is at its lowest and the marginal utility of cash is at its highest. Therefore, they conducted an experiment, which allowed farmers to postpone the payment of insurance premium after harvest. Their result show that this help relaxing the liquidity constraint of the farmers and resulted in an increase in the uptake of index-based insurance.

When there is a high transaction cost in accessing the market, this could hinder the adoption of agricultural technology by smallholder farmers. In the study by Suri (2011), the poor market infrastructure made the adoption of hybrid maize in Kenya unprofitable. To address this issue, McIntosh (2016) proposed the development of IT platform for agricultural products. This platform helped improving the prices received by farmers and creating rewards to quality improvements.

For the supply-side constraints, the main focus is on information on new agricultural technology. According to Beaman et al. (2018), information frictions are potential constraints to technology adoption, and social relationships can be an important channel through which smallholder farmers learn about and are convinced to adopt new technology. They conducted a randomized controlled trial in Malawi to specify a model of learning, comparing between theory-driven network targeting approaches to simpler strategies that rely on a government extension officer. Their result shows that technology diffusion is characterized by a complex contagion learning environment in which most farmers need to learn from multiple people before they decided to adopt new technology. Thus, strategically selecting early adopters can make a difference for social learning.

4.2.1 Lab in the field experiments

To better understand how to increase technology adoption among small scale farmers, we design lab in the field experiments to answer 1) whether liquidity constrains prevent technology adoption, 2) whether we can improve new technology adoption through social learning by involving farmers closer to the target population as promoters, and 3) could the risk transfer mechanism through provision of subsidies help alleviate the problem of loss aversion, which hinders the adoption of new technologies.

To answer to these questions, we create a multi-arm of study involving three cross-cutting sets of treatments, which can be separated to 1) liquidity constrains treatment consisted with two experimental groups, 2) social learning treatment consisted with four experimental groups, and 3) subsidy treatment consisted with four experimental group. There are therefore ten experimental groups in total. Figure 29 describes the three treatment arms. The details of each experimental arm are as follows.

Figure 29 here

Liquidity constraint experimental group

To test the effect of liquidity constraint on adopting new technology, this experimental arm consists of two subgroups with different levels of endowments. Subjects in one subgroup receive low endowments and those in another group receive relatively high endowments. Subjects in the low endowment group are allocated 3 rai of land, 20 Baht initial saving and 60 Baht initial debts, while the high endowment subjects are allocated 5 rai of land, 60 Baht initial saving and 40 Baht initial debts.

The smaller the land size suggests the lower the income subjects could have from each cultivation season (round) and vice versa. Saving reveals the ability of investment and absorb shock. Lower the saving means limit ability of investment and absorb shock from income loss according to crop fail. Debt affects the net income subjects will have from experiment. It would have psychological impact on subjects because higher the debt would result in lower net income they have from the experiment.

The difference of endowments would affect decision to adopt the new practice because subjects with low endowments face limit risk absorption (saving), limit income generation (land size), and debt constraint when compared to those in the high endowment group. This would result in low rate of new technology adoption for the low endowment subjects. However, the impact of liquidity constraint would be less intense if the decision whether to adopt the new technology is dominated by behavioral factors.

Enhance technology adoption through social learning experimental group

To test whether we can improve new technology adoption by involving farmers closer to the target population as promoters, this experimental arm contains four subgroups with differences endowment levels and sources of information. There are two groups of subjects with different endowments, which is the same as in the liquidity constraint group. In addition, subjects in this experimental group receive decision information in each round from a success farmer before they make decision in each round. Subjects are told that the decision information comes from a subject in another experimental group who receives the highest payment. There are two success farmers. The difference between these success farmers is endowments. The first one has high endowments. The level of endowments is the same as subjects in the high endowment group. The second success farmer has low endowments, which is the same level as subjects in the low endowment group. The endowments information of success farmers is presented together with their decision information to the subjects in every round. This is to make sure subjects would compare their status (through endowments) with the success farmer. The differences between subjects' endowments and sources of information create four experimental group in this arm as follows

a) Low endowments subjects receive decision information from a low endowments success farmer. (Low endowment_GF)

b) Low endowments subjects receive decision information from a success high endowments farmer. (Low endowment_LF)

c) High endowments subjects receive decision information from a success low endowments farmer. (High endowment_GF)

d) High endowments subjects receive decision information from a success high endowments farmer. (High endowment_LF)

The decision comparison between group a) and group b) provides answer whether low endowment subjects follow the success farmer who is the same or better than them. The same pattern can also be check for high endowment subjects by comparing decision between group c) and d). These comparisons allow us to find the answer of if we want to improve a new technology adoption through social learning what type of communicators or promoters (farmers) should we focus.

Enhance technology adoption through one-time subsidy to reduce loss aversion

This experimental arm also starts the same as another arms. There are two groups of subjects with different endowments, low and high endowments. To test whether temporary subsidy could reduce loss aversion and enhance new technology adoption, subjects in this group are told that they will receive subsidy for the first time of adopting the second practice that provides higher return and higher risk. The subsidy is one-time subsidy where subjects receive the subsidy in only one round.

We aim to test the impacts of different forms of subsidies on enhancing new technology adoption. We focus on two forms of subsidies, which are subsidy for production cost and subsidy for income. For the subsidy for production cost, subjects receive additional money that can cover the production cost for the first time of adopting the new practice. This subsidy provides some risk absorption from adopting the new practice that contains high risk (50 percent) of getting no income. The subsidy ensures that they still have investment money to invest in the next season (round) even they fail in the first time of adoption. For income subsidy, subjects receive additional money equal to income they would have earned from growing conventional practice in the first round of adopting the new practice. The income subsidy, in our view, should be more attractive when compared to the cost subsidy. This is because first the income subsidy guarantees subjects still receive income they currently have from the conventional practice, which should be their reference. Second, they could earn more income from the new practice if it succeeds. From these two reasons, subjects have nothing to lose from adopting the new practice. Hence, they may not see the new practice as the risky choice.

From two different endowments and two different forms of subsidies, this experimental arm contains four groups of experiment as follows

a) Low endowments subjects with cost subsidy. (Low endowment_Cost)

b) Low endowments subjects with income subsidy. (Low endowment_Income)

c) High endowments subjects with cost subsidy. (High endowment_Cost)

d) High endowments subjects with income subsidy. (High endowment_Income)

In all three arms, the experiments start with all subjects are given endowments, which are the combination of agricultural land size, saving, and debt. These endowments represent the resources and constraint farmers need to consider before making decision on agricultural activity (in experiment).

Subjects are asked to make decision to choose between two rice cultivation practices. The first practice is framed as conventional practice that is routinely practiced by the subjects. This means the risk of getting no yield is low, 20 percent. However, the return of the conventional practice is also low. Another practice is framed as the new practice where the new technology is employed to increase productivity resulting in higher return on investment than the conventional one. However, the risk of getting no yield is relatively high especially during the early state of adoption. The risk of crop failure for the new practice is 50 percent in the first season (round) of adoption as the farmers are initially unfamiliar with the new practice. The risk declines to 40 percent and 20 percent if the new practice is continued to the second and third seasons (round) or more, respectively. Note that when subjects select the new practice they have to continue this practice for at least three seasons (rounds). The returns, costs, and risks of these cultivation practices are presented in Table 7

Table 7 here

There are ten rounds of experiments represented ten cultivation seasons. In each round, subjects have to make decision which type of practices they want to apply. After choosing the practice in each round, determining whether subjects receive income in that round depending on the results of drawing a Ping-Pong ball from a box that represent the risk of getting no yield from each practice. There are two color of Ping-Pong balls, white and orange. The white ball represents the situation that there is no crop failure taking place so participants can sell their outputs and receive payoff. However, if the orange ball is drawn, this indicates there is crop failure thus participants will not receive any payoff.

There are four boxes represent different risks of getting no income. For conventional practice, there are eight white balls and two orange balls. This represents the 20 percent risk of getting no income from conventional practice. There are five white balls and five orange balls represented 50 percent risk of getting no income for the first time of adopting the new practice. Another box contains six white balls and four orange balls represented 40 percent risk of getting no income for the second season (round) of adopting the new practice. The fourth box contains eight white balls and two orange balls indicated 20 percent risk of getting no income for the third season (round) or more for the new practice. In any round, if the participant is running out of liquidity (i.e. having insufficient money to make investment), the subjects have to borrow equals to the amount of investment in that particular round without any interest charge. The initial debts and the additional loans need to repaid at the end of the experiment.

After the 10^{th} round is over, each subject receive payoff equals to the cumulative profit at the end of the 10^{th} round net of initial debts, additional debts incurred during the experiment and initial saving.[4] This mechanism is set to make sure the subjects make

[4] Subjects also receive 100 Baht to compensate their time for joining the experiment, and this are told during recruiting process. In addition, if subjects have negative income after deducting debt and saving, they do not need to pay any money to us and receive 100 Baht as their time compensation.

decision in each round carefully because it affects amount of monetary reward they will get from the experiments.

4.2.2 Data and estimation

The experiment was conducted during 17th – 29th August 2019 in Pathumthani and Kalasin provinces. Pathumthani and Kalasin are the provinces in the Central and Northeastern Regions of Thailand where rice is widely grown. In total, 405 rice farmers participated in our lab-in-the-field experiment, comprising of 205 farmers from Pathumthani province and 200 farmers from Kalasin province. The sampling process can be summarized as follows. First, we obtain the statistics of rice growing sub-districts in each province. Next, we select the top 4 sub-districts with highest areas of rice cultivation. In each sub-district, we then randomly select the villages.

Given that the data obtained from the lab-in-the-field experiment has multilevel or clustered structure due to the longitudinal nature, an approach used to analyze such clustered data is the use of random effect regression analysis. Provided that the outcome variable in this study is a decision whether to adopt new agricultural technology, the outcome variable is in a dichotomized manner or considered as a binary outcome. Thus, the model specification to be estimated is a logistic random effect model (Li et al., 2011). A binary logistic random effect model has a binary outcome ($Y = 0$ or $Y = 1$) and regresses the log odds of the outcome probability on various predictors to estimate the probability that $Y = 1$ happens, given the random effect. The dichotomous two-level model is given as follows:

$$ln\left(\frac{P\left(Y_{ij} = 1 \middle| x_{ij}, u_j\right)}{P\left(Y_{ij} = 0 \middle| x_{ij}, u_j\right)}\right) = \alpha_1 + \sum_{k=1}^{K} \beta_k x_{kij} + u_j$$

$$u_j \sim N(0, \sigma^2), j = 1,2,\ldots,10 \qquad i = 1,2,\ldots,n_j$$

where $Y = 1$ if the individual adopts new practice and $Y = 0$ otherwise, i represents individual farmer, and j represents round of the experiment.

4.2.3 Results of lab in the field experiments

Full comparison across experimental arms

We start testing the full comparison of all treatment arms. Table 8 presents the estimation results of all treatment arm. The liquidity constraint high endowment group is used as reference. The result suggests that liquidity constraint would not be the barrier to prevent participants to adopt the new practice. This is because the decision of low endowment participants is not significant different from that of high endowment. As mentioned earlier if the liquidity constraint has no impact on adoption decision behavioral factors would be the key.

Next, we move to the social learning experimental arm. Generally, the decision to adopt the new practice in this arm is not significantly different from those of the liquidity arm. However, low endowment subjects receiving information from the high endowment success farmer (Low endowment_LF variable) seems likely to avoid adopting the new practice. We will go in to further details of this result in the social learning section where the analyses are break down to pair comparison.

The final experimental arm is subsidy group. The result from this group clearly suggests that subsidies both cost and income would enhance new practice adoption. The coefficients of three out of four experimental groups are positive and significantly different from reference group (high endowment in liquidity constraint experimental arm) suggesting when the subjects receive one-time subsidy (either cost subsidy or income subsidy) they are more likely to adopt the new practice. Again, we will go in to the details of this experimental arm when the pair comparison analyses are employed. Note that we find no different preference between subjects from Patumthani and Kalasin provinces at least in this model specification because the region variable captured this effect is statistically insignificant.

Table 8 here

Social learning

We now move to the details of social learning, and analyze the new practice adoption by focusing on the impact of social learning through the difference of promoters, the general farmer (GF) and the lead farmer (LF). The decision of adopting the two different practices now is a function of interactions between different endowments and different sources of information from either the GF farmer or the LF farmer. Table 9 presents the results of five model specifications. The full model shows the overall impacts of these combinations. Note that the subjects with high endowment and receive information from lead farmer (High endowment_LF) is reference. The result of the full model indicates generally differences in either subject's endowments or information receive seem to not affect the decision to adopt the new practice. Specifically, subjects with low endowment and receive decision information from the general farmer (Low endowment_GF) and subjects with high endowment receive decision information from the general farmer (High endowment_GF) would not have different rate of adopting the new practice when compared to the subjects with high endowment and receive information from lead farmer. However, when subjects with low endowment receiving information of the high endowment success farmer (Low endowment_LF), they tend likely not to follow the success lead farmer.

Next, we move to the pair comparisons where the decision of subjects with the same endowment but receiving different information and the decision of subject with different endowments but receiving the same information are compared. We start this part with the result of "Low endowment" specification in column 3 of Table 9. This specification is estimated to test the effects of information from different success farmers on the decision of low endowment subjects. The low endowment subjects receiving information from lead farmer (Low endowment_LF) is used as reference. The result suggests that even the coefficient of the Low endowment_GF variable is positive but it is not statistically significant suggesting no impact of different information on decision for low endowment subjects. The story is also the same for the high endowment subjects receiving information from different success farmers ("High endowment" specification in column 4).

We also analyze the decision of subject with different endowments but receiving the same information. The results of this analysis are presented in "GF" specification in column 5 and "LF" specification in column 6. When low and high endowment subjects receive decision information from success general farmer, their decision to adopt the new practice is statistically insignificant ("GF" specification). However, when low endowment subjects receive decision information from success lead farmer, they seem likely to not follow when compared to the high endowment subjects receiving the same set of information ("LF" specification).

In sum, we do not find clear patterns of social learning on the new practice adoption. However, we do find that if we want to speed up technology diffusion using social learning we may at least need to avoid using communicators who have better status than our targets.

Table 9 here

Loss aversion through different forms of subsidy

We now move beyond social learning, and compare the impacts of one-time cost subsidy and income subsidy. The decision of subjects now is a function of interactions between different endowments and subsidies. Table 10 presents the results of five specifications. The first specification named "Full model" presents the full explanation of the subsidies on decision whether to adopt the new practice. The high endowment receiving income subsidy group is used as reference. The full model suggests that subjects with low and high endowments are more likely to adopt the new practice when either cost or income subsidies are offered to them. When we compare whether there is different impact between cost and income subsidies for low endowment subjects we found no difference ("Low endowment" specification in column 3). However, we do find the different impact of these two forms of subsidies for the subjects with high endowments ("High endowment" specification in column 5). Namely, the cost subsidy seems to convince subjects in this group to adopt the new practice more than the income subsidy.

We next analyze the decision of subjects with different endowments but offered the same subsidy. The "Cost" specification reveals the impact of cost subsidy on the decision of subjects with high and low endowments. The subject with high endowment group is used as reference. The result shows that the impact of cost subsidy is statistically indifferent between these two types of subjects. Finally, we do the same thing for the income subsidy. Decision whether to adopt the new practice is now as a function of subjects with different endowments and offered the same income subsidy. The result is different from the cost subsidy in which the low endowment subjects seems to be more convinced to adopt the new practice than the high endowment subjects when the income subsidy is offered ("Income" specification in column 6).

All in all, the results in this section clearly reveal that the either forms of temporary subsidies could significantly improve the new practice (technology) adoption especially for the low endowment subjects. In addition, combined with the result of liquidity constraint, the results also point to loss aversion would be the key barrier to prevent subjects to adopt the new technology

Table 10 here

4.2.4 Extension to the real setting: Results from the randomized control experiment

The results presented earlier are obtained from the lab-in-the-field experiment. What would happen if the experiment were extended into a real or natural setting? The Royal Initiative Discovery Foundation have implemented new crop program to farmer in 38 villages of Kalasin province to increase income of farmers since 2015. The new crop project focuses on persuading farmers to grow new crops, which provide significant higher benefit than off-seasonal rice that is regularly grown during dry season (January to May). In the first year of project, the foundation offered a menu of crops that the farmers can choose from.[5] Farmers received inputs for crop production, including seeds, fertilizer and other inputs. The costs of all inputs will be repaid when the crops are sold. However, if the revenue from selling the crops cannot cover the input cost, the foundation bears the loss. An experienced supervisor was assigned to each farmer. This supervisor had regular visits to the farmers' farms to educate and help the farmers to solve farming problems. The foundation purchased all products under this program to ensure farmers that there is secure market for their products. In the first year of the program, there were 48 farmers joining the program. The number of participants was lower than the foundation expected. The program continued to the second year in 2016 because the foundation expected that the number of farmers joining the program would increase after seeing the results of the program from the first year. However, the number of participants in the second year of the program was still low. The number of participants actually reduced to 46 farmers.

Being motivated by the low rate of adopting for the new crop program, Mahasuweerachai et al. (2018) conducted a study, supported by the Royal Initiative Discovery Foundation, to find the way to increase the rate of adoption for this program. The study first identified the main barriers that hindered the adoption of new technology. Focus groups discussion and short survey with farmers to collect information what should be key barriers preventing farmers to try the new crops were implemented between July and August 2016. The main results from the survey suggested that farmers are risk averse agents especially in the context of agriculture. In addition, they were more concerned about downside risk. Namely, many of them would not adopt a new crop or technology that could on average provide 50 percent increase of the yield or income with 10 percent chance of getting nothing, for example. This indicates farmers pay extra attention to losses

[5] There are three crops, which are maize, sweet corn, and chilli. Farmers were allowed to choose no more than two crops.

compared to gains. This behavior is well known as "loss aversion", a key element of Prospect Theory (Kahneman and Tversky, 1979). The focus group discussions provided us fruitful qualitative information what would be insight the mind of farmers that leads them to weight their decision more on losses. The loss aversion led to risk aversion would likely come from the uncertainty of their household economic status. The farmers in this area are not absolute poor. In another word, they have enough income to feed family. However, they have high debt and very low saving. Many of them stated during focus group sessions the benefits from new crops introduced by the foundation are good. However, they would have had those benefits from growing them only if they could get good yields from the cultivations, which they were not sure because they never grow them before. In addition, they need to spend more time in agricultural filed to learn and take care the new crops. This means less time to go working outside the field to get extra income, which they always do during the dry season. The information from the survey and focus group lead us to believe that most farmers would see the new crops introduced by the program as risky choices and try to avoid them.

Because loss aversion would be the key barrier, we therefore developed the risk transfer mechanism, and employed it together with other measures of the program implemented in the two years earlier. The risk transfer mechanism includes the payment of 5,000 Baht per month over the 4 months during the off-season farming period. This payment did not completely work as subsidy because the farmers still need to repay this money and input cost to the foundation after selling the crops. When the entire loan amount has been repaid and there is no outstanding debt, all profit will be incurred to the farmers. However, if the farmers' revenue does not cover the total costs, i.e. input costs and monthly income insurance, the foundation will cover the loss. And, the farmers still have monthly payments. To alleviating the moral hazard problem, an supervisor assigned to educate and help farmers in the field also monitored whether farmers put in enough effort on farming. If the farmers do not put in enough effort, they will not receive payment for the rest of the period.

This mechanism would eliminate or at least reduce the impact of loss aversion because it ensures farmers they will still have income when joining the program. In addition, the mechanism would encourage farmers to spend more time in the field because the concern of having not enough income to spend for family matters was diminished. Note that this payment was one-time support. Namely, farmers had this income insurance for the first year of adoption only. If they want to continue in the second year or more, they will not receive the income insurance but still have other supports from the foundation, i.e. inputs and market supports. This setting also allows us to track whether the temporary risk transfer has long-term effects on new crops adoptions.

Program Implementation

The program was implemented in 38 villages between late October to the end of November 2016. The process of recruiting participants is as follows

- The recruitment was done in village level.
- The foundation staffs contracted village heads to make appointment with all villagers.
- The foundation staffs and us provided information of the program to the villagers.
- The villagers had three day to make decision to join the program.

Note that the number of participants in each village was limited to 10 households.[6] If more than 10 households registered lottery or a village head was used to select 10 participants.

Program Results

The measurement outcome of the temporary risk transfer mechanism was the number of applicants after the mechanism was employed. If the numbers of applicants before and after the mechanism implemented are not different the loss aversion would not be the key barrier to prevent the farmers to adopt the new crops as we expected. However, if the numbers of applicants are different it would be highly possible that the loss aversion would be a major obstacle for farmer to adopt the new crops, and providing them with risk transfer mechanism would increase adoption rate.

The result shows that the risk transfer mechanism works well in solving the fear of loss or loss aversion among farmers, encouraging more farmers to register in the program. There were 318 households applied for the program, substantially higher than before the risk transfer mechanism was introduced.[7] From the result, we first conclude

[6] There was another study to find the impact of limited resource massage on the number of applicants. In this study, the villages were divided into three groups, which was one control group and two treatment groups. Subjects in the control group were not told during the meeting the number of participants was limited to 10 households per village. On the other hand, subjects in treatment groups were told this information during meeting. The difference between the two treatment groups was the selection criteria if more than 10 households applied for the program. Lottery was used to select participants in one treatment. For another treatment, participants were chosen by a village head if more than 10 households apply.

[7] Among 38 villages, there were 3 villages that had no applicants.

that loss aversion would be a key barrier to adopt the new crops. Secondly, the risk transfer mechanism could reduce the impact of loss aversion and provides farmers incentive to try the new crops.

After having 318 applicants, the foundation staffs checked whether each applicant had enough water supply during the dry season to grow the new crops. This process reduced eligible farmers to 264 for lottery selection or chosen by a village head process. The final number of farmers participated in the program in the dry season of 2017 was 200 farmers (please see Figure 30). This number is still significantly higher than those before the risk transfer mechanism implemented. After the cultivations started in January 2017, 19 participated farmers were eliminated from the program because they did not put enough efforts in farming. This reduce the number of farmers in the program to 181, and all stayed in the program through the end of season.

Figure 30 here

The profits farmers receive from the 2017 season were low. The average profits per households of the new corps in 2017 are presented by the orange bars of Figure 30. The low profits did not surprise us because more than 70 percent of the participated farmers have never grown these crops before. In addition, even though the farmers were visited by the field experts from the foundation every week, the efficient communications and trust seems not to fully establish. Some suggestions from the field experts were ignored, and the farmers tried other techniques that they believed should provide better outcomes, for example.

The program started again in the dry season of 2018. The details of the program were the same as those in 2017 except there was no income insurance and no limit number of participants. The foundation staffs started to recruit the farmers to the program between late September to the end of October, which was a bit earlier than 2017 season. The information of no income insurance was clearly stated during the village meetings. Out of 181 farmers who joined and finished the program in 2017, 154 farmers, which was about 85 percent, joined the program in the 2018 season (please see Figure 29). In addition, there were 98 new farmers joining the program.

The reasons given to us by farmers who joined the program in 2017 of why they continued in 2018 even many actually loss or get slim profits was first they know how to grow the new crops to get good yields. Second, they know that the new crops really provide higher profit than off-seasonal rice. However, we do not know exactly why the new 98 farmers joined the program even they known there will not have income insurance. One reason that may be possible is the power of social learning. The new farmers may observe or talk what their neighbors who joined the program in 2017 did and found the activities were interested and wanted to try them. It may also be possible that most farmers who joined the program in 2017 were general farmers. This means they were the representative of the general population and experience similar conditions as majority in the villages. There are recent studies found that diffusions of information and new products through social learning would be greater if the receivers and promoters share similar conditions and experiences (Bollinger and Gillingham, 2012; Mobius and Rosenblat, 2014; Benyishay and Mobarak, 2018). To find whether social learning or something else causes the relatively high adoption rate for the new participants in 2018 the controlled experimental studies would be suitable to provide us the answer.

We now turn to the profits of the new crops in 2018 season. The profits of the new crops in 2018 are presented by yellow bars in Figure 31. Interestingly, the average profits per household for each crop are significantly higher than those in 2017. The average profits increase more than double in every crop given the average land sizes per household to grow these crops are not different between two seasons.

Figure 31 here

Takeaways

Our lab in the field experiment already reflects the fact that behavioral factors affect adoption of new agricultural practice more than liquidity constraint. We found that some forms of social learning and interventions to relieve loss aversion could be effective in enhancing technology diffusion. Even though, the results from our experiments could not clearly determine whether farmers follow advices from technology communicators who share similar conditions with them, we found promoting lead farmers (high endowment farmers) as communicators would reduce the rate of adopting technology especially if the target famers are the general farmers who have low endowments or face more difficult conditions than the lead farmer. From our experimental results, the loss aversion is more likely the main obstacle preventing farmers to try the new practice. To overcome the loss aversion, temporary subsidies especially in the early state of adopting the new technology would be very crucial.

The result of field study involving real world setting conditions confirms the results of lab in the field experiment. Loss aversion could hinder the adoption of new agricultural technology among smallholder farmers. However, the form of subsidy now matters. Subsidy in form of production cost does not alter adoption decision. While, the income subsidy significantly increases adoption rate.

The key takeaways from results from lab in the field experiments and field study provide us insightful farmers mind. The first think is if we want to overcome loss aversion to enhance technology adoption temporary income subsidy would be crucial to incentivize farmers to adopt new technologies. Secondly, incorporate this incentive with social network through social learning may be another potential channel to enhance cost-effective technology diffusion. Given incentive matter and social transmission is not always automatic, we may need to find proper injection points of incentive within a social network to do initial experimentation and communication. This communicator then helps to spread out the technology to target populations. The main question that still cannot clearly be answered by this study is what characteristics of the communicator. We do know, however, the communicators who would lead faster adoption should not be too far better in term of economic conditions and agricultural conditions than the target farmers. This kind of extension program would be highly cost-effective because network-based communication and other forms of peer effects are already present in the communities. This kind of program may also be more effective than having extension workers from outside to regularly visit a community.

Conclusions and policy implications

Our paper identifies several challenges facing Thai agriculture including small landholding, inequality in land ownership and access to necessary water resource, increasing vulnerability to climate risk and climate change, rapidly aging farmers, low and slowing productivity and value added, increasing production costs and the cost-revenue structure that are increasingly vulnerable to the world market and finally incentive and market distortion due to policies.

We have also identify several opportunities including higher education especially among young labors, concentration of production that allow for various gains from economies of scale and development of technology and innovation for agriculture.

Policy priorities toward making our farms, farmers and farming competitive, resilient and sustainable thus should focus on (1) stimulating smallholder farmer's adaptation and adoption of technology and innovation, (2) promote access to necessary resources, i.e., land ownership, water resource and necessary safety net programs and (3) transforming incentive/market distorting policies into incentive linked policies. And we identify three key enables including technology, behavioral insights and data.

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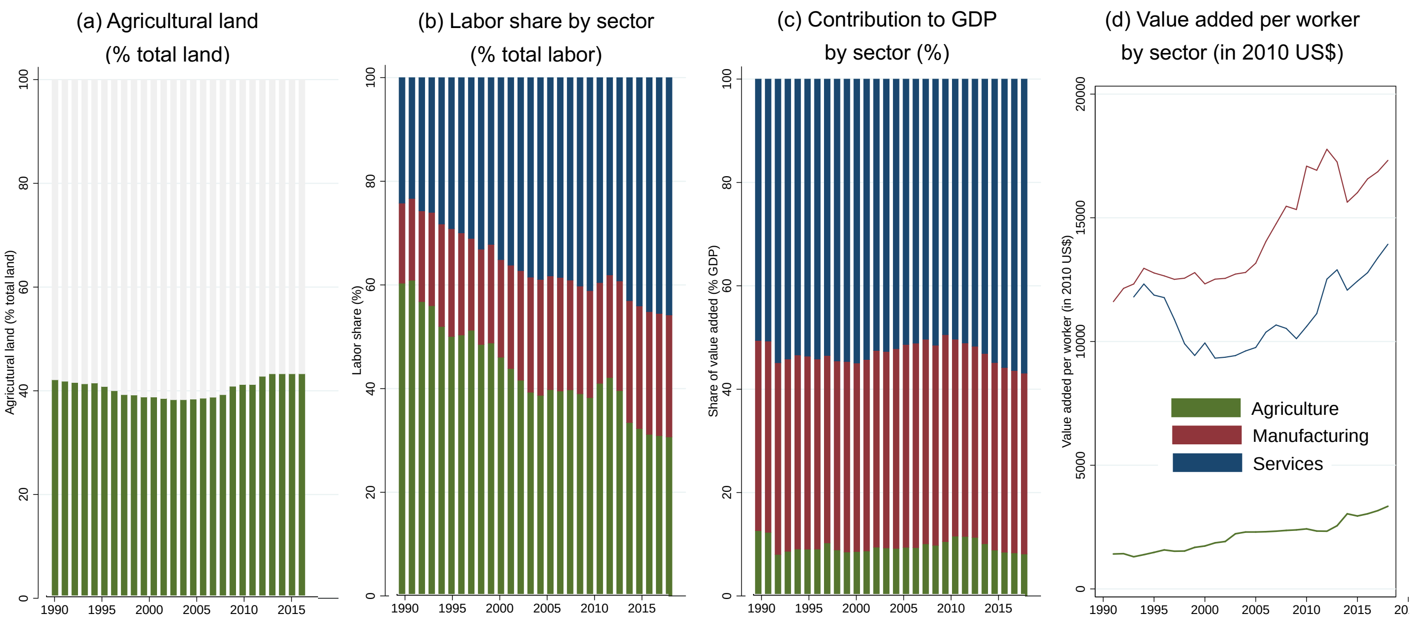
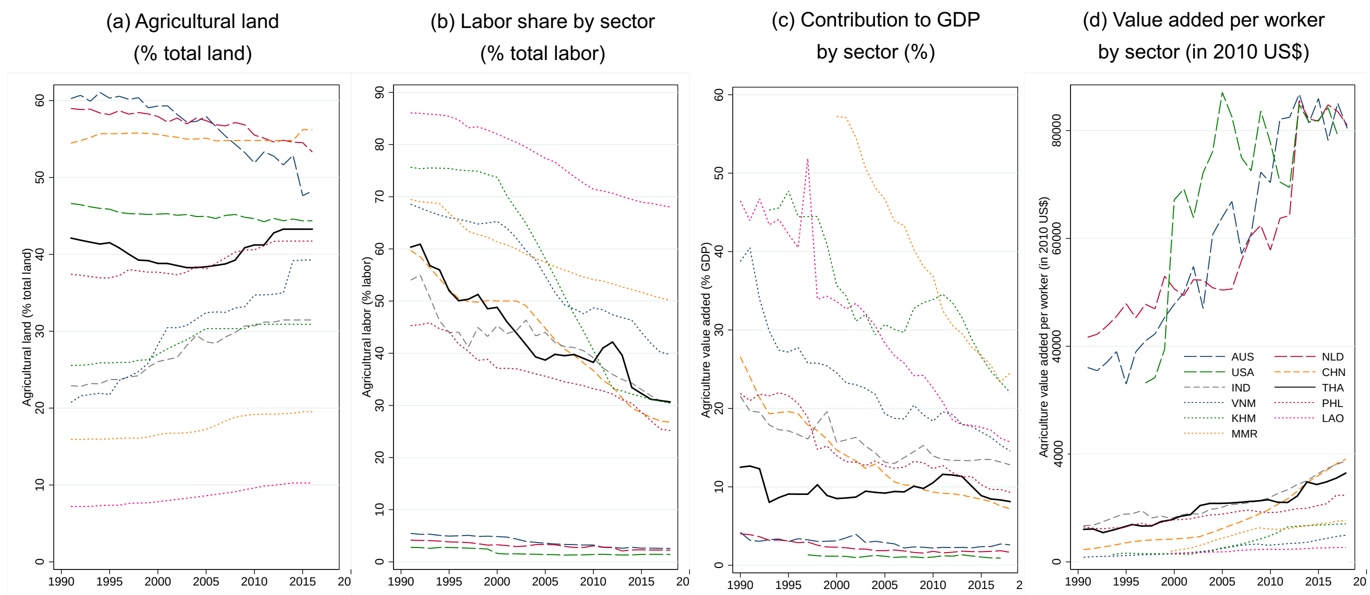
Figure 1: Agriculture in Thai Economy



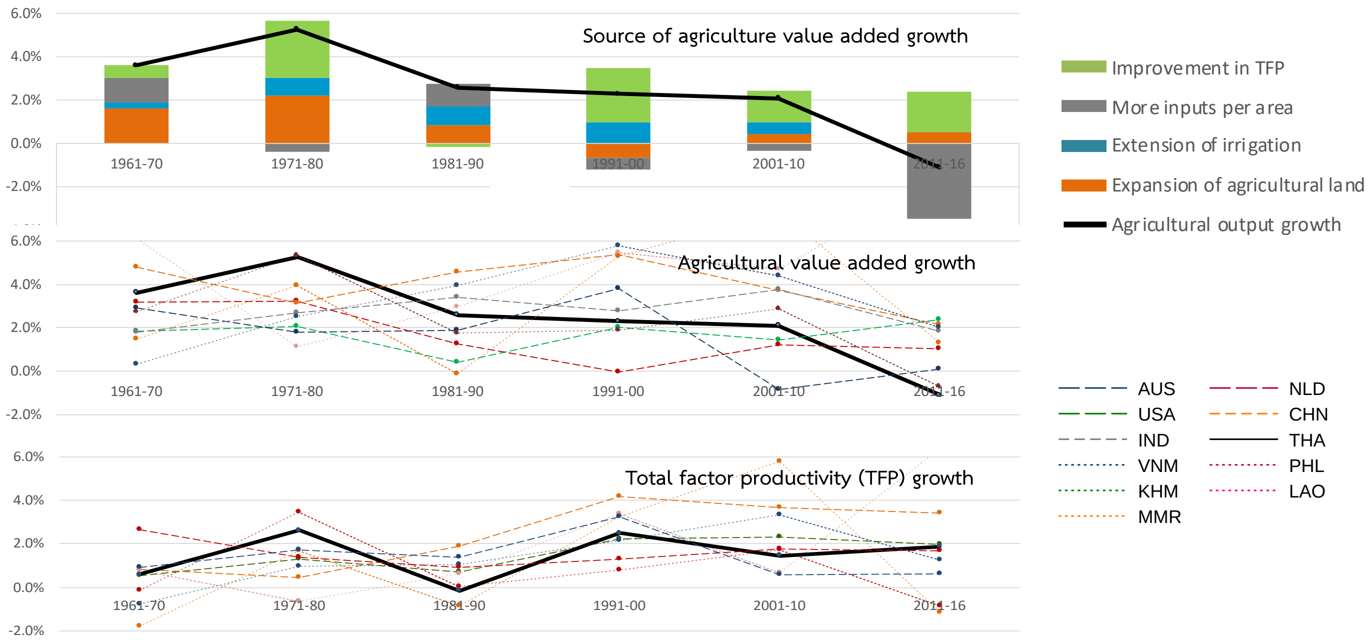
Data source: World Bank Development Indicator Index

Figure 2: Thai Agriculture relative to the rest of the world



Data source: World Bank Development Indicator Index

Figure 3: Source of Thailand's Agricultural Value-Added Growth over the past 60 years



Data source: International Productivity Data, USDA Economic Research Service

Figure 4: Thailand's export share in the world market for key crops

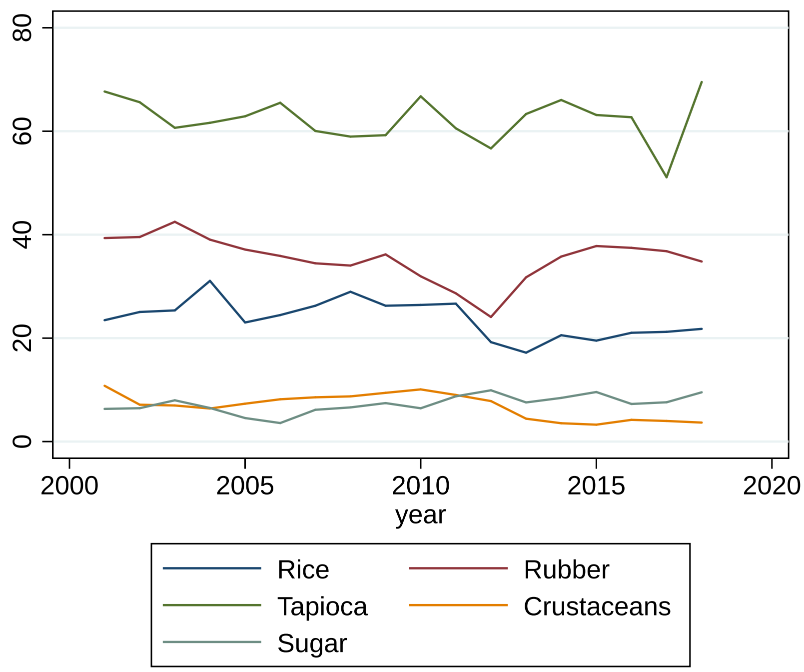
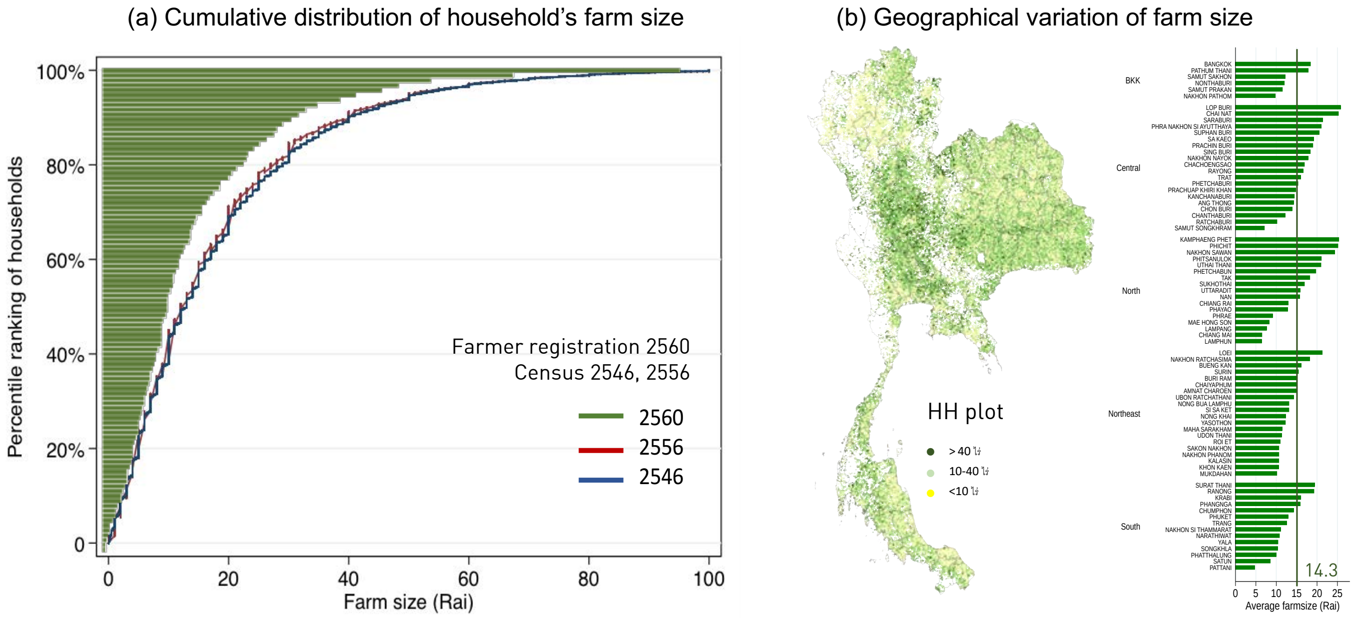
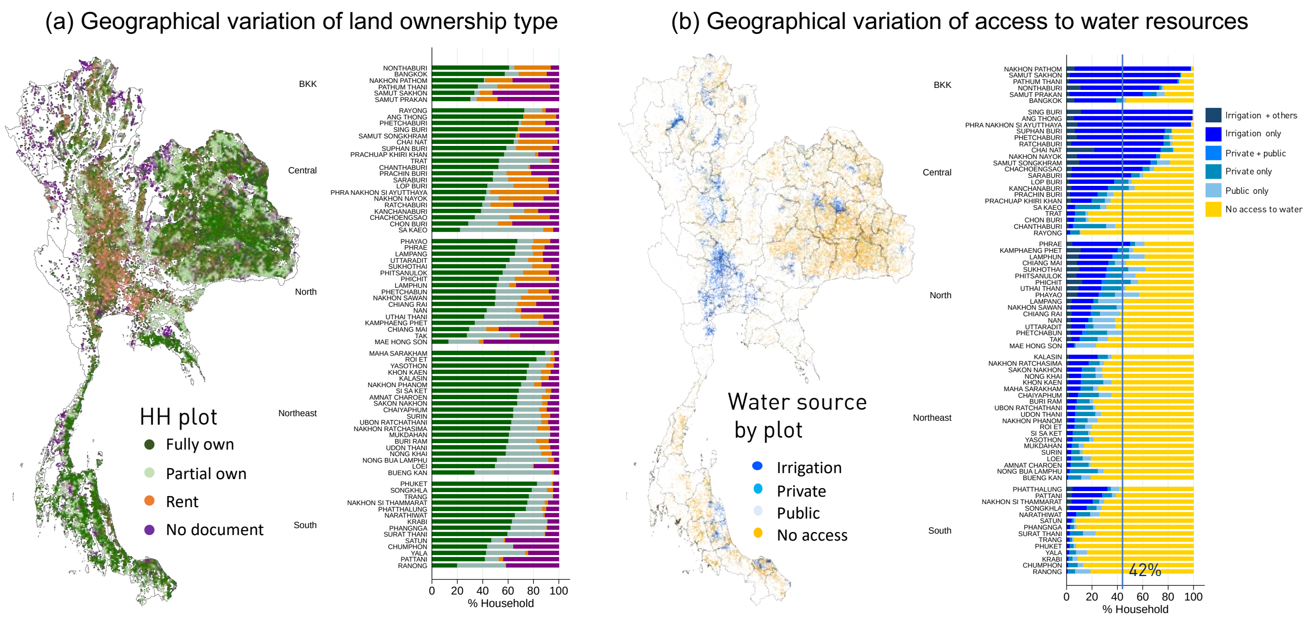


Figure 5: Farm Size



Data source: Farmer registration 2560, Census 2546,2556

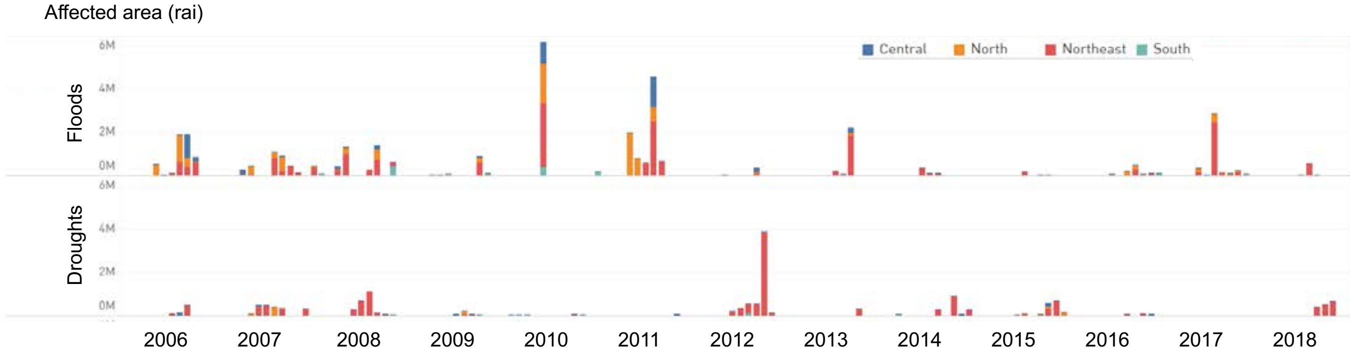
Figure 6: Land Ownership and Access to Water Source



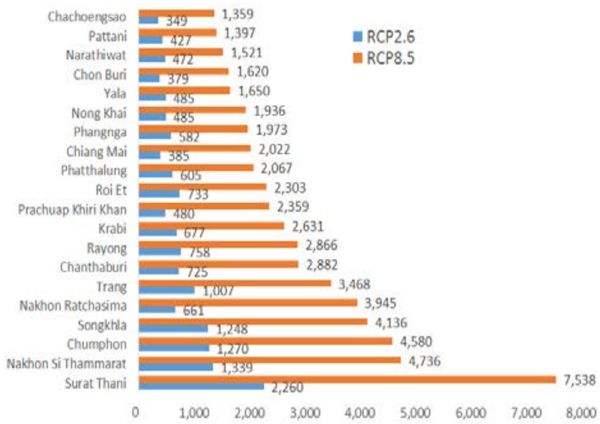
Data source: Farmer registration 2560

Figure 7: Estimated Climate Change Impact on Thai Agriculture

(a) Disaster affected agricultural areas (2006-2018)

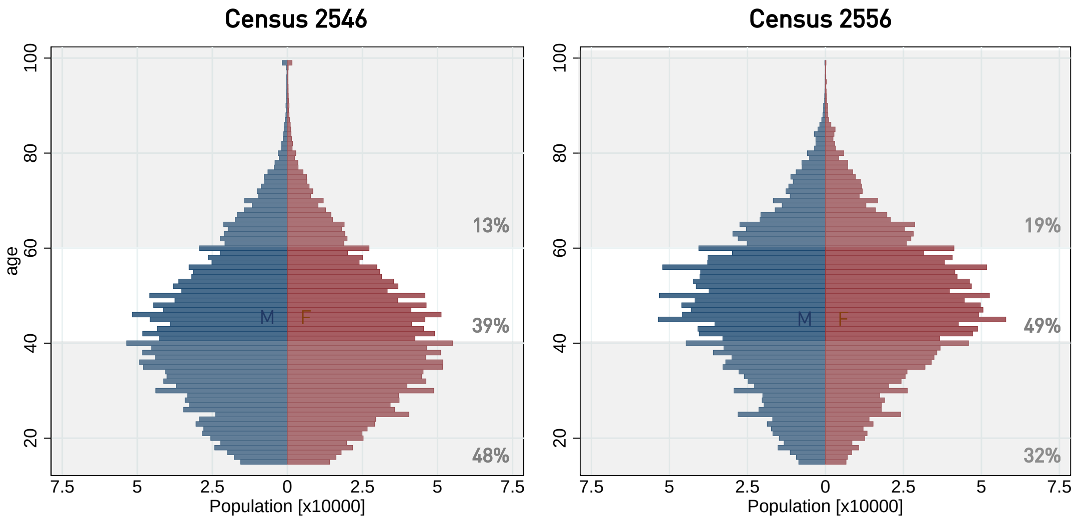


(b) Accumulative damage values from climate change
(top 20 provinces from 2011-2045, million)



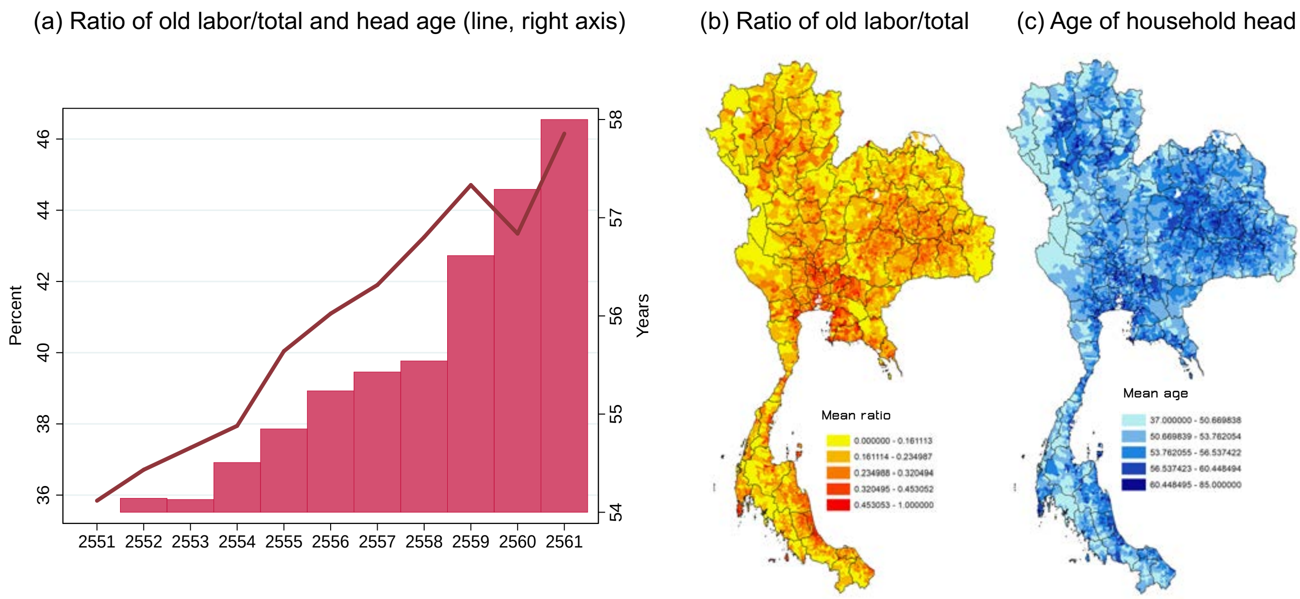
Data source: (a) Department of Agricultural Extension, (b) Attavanich (2017)

Figure 8: Labor in Agriculture by Age and Gender



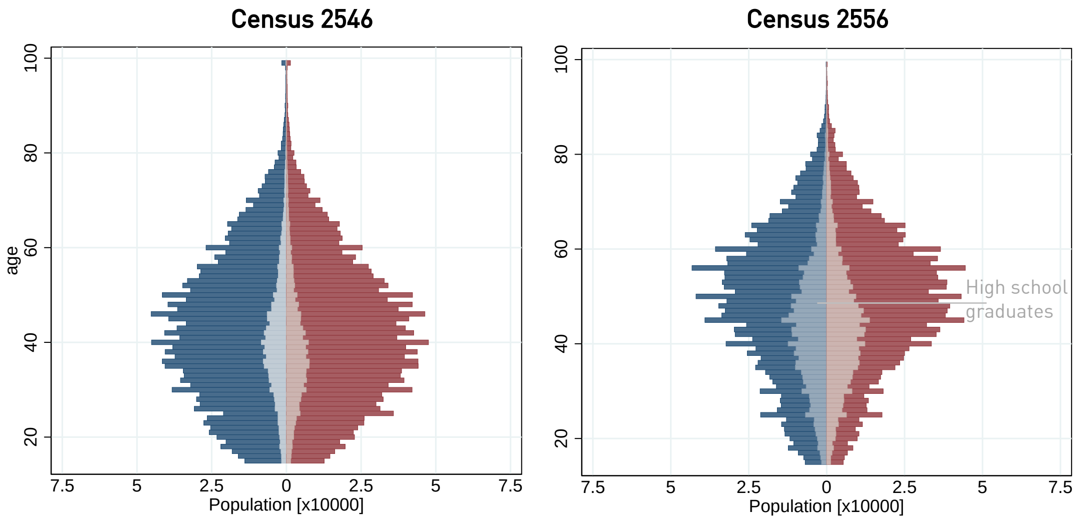
Data source: Census 2546, 2556

Figure 9: Aging Situation in Agricultural Households



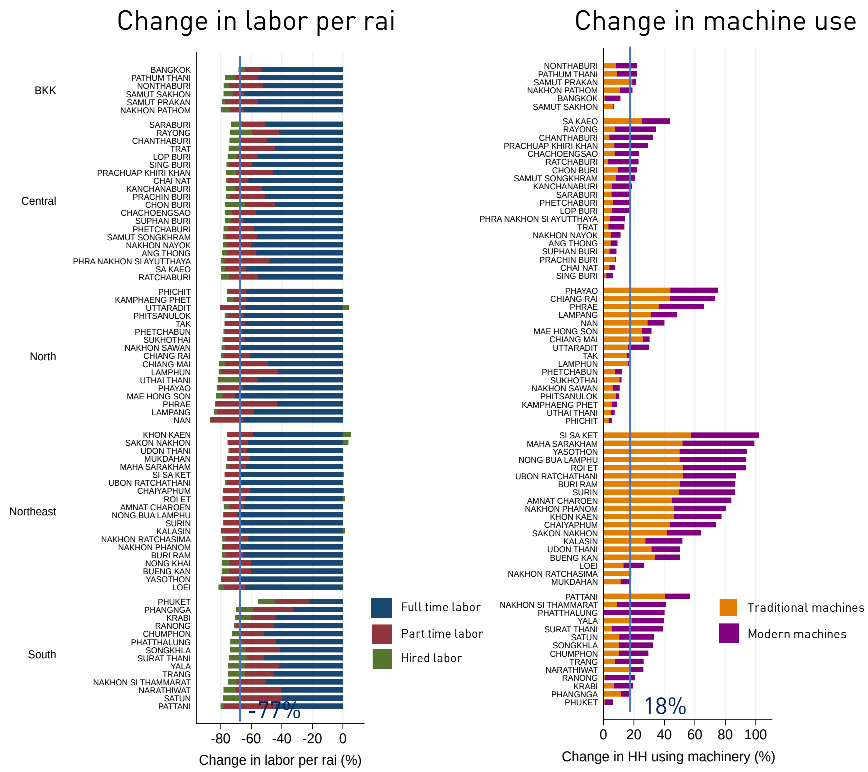
Data source: Agricultural household survey 2551-2561, Census 2556

Figure 10: Education Status of Agricultural Labor



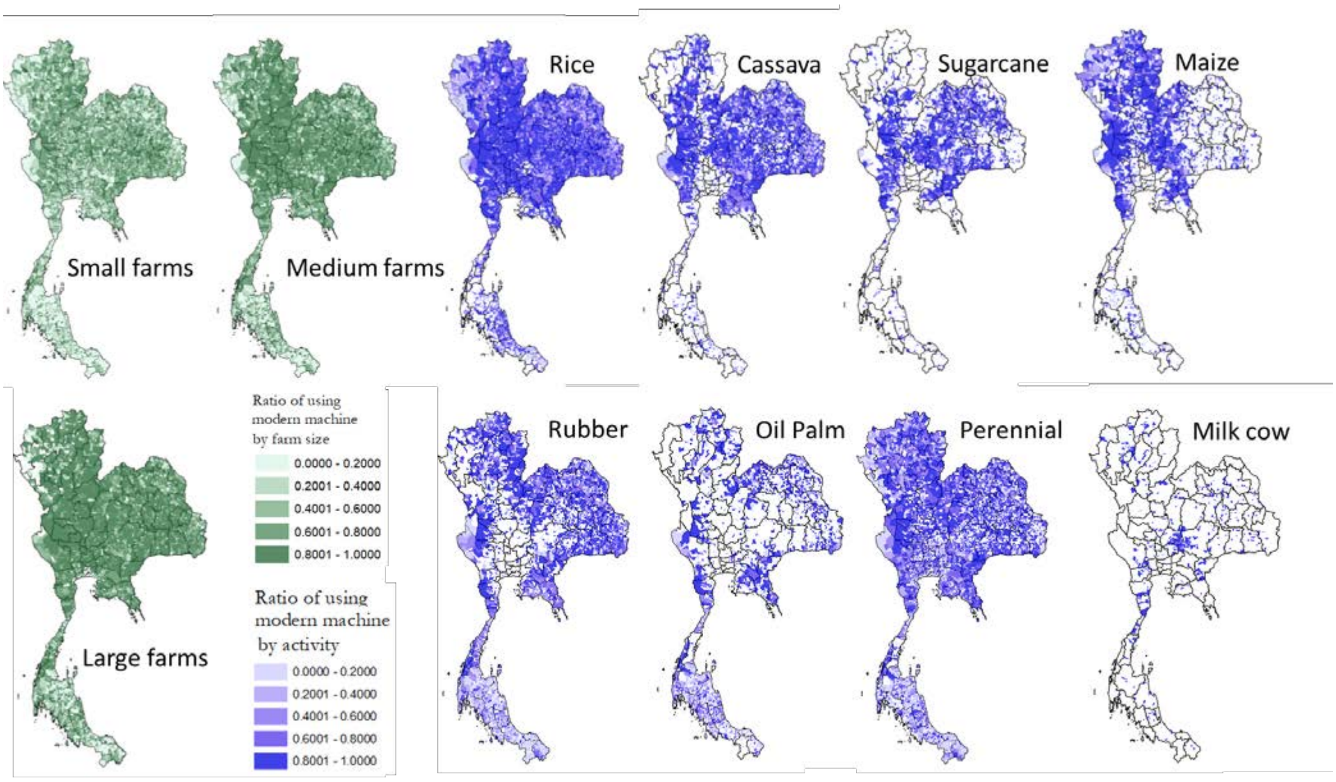
Data source: Census 2546, 2556

Figure 11: Structural Transformation in the Use of Labor and Capital



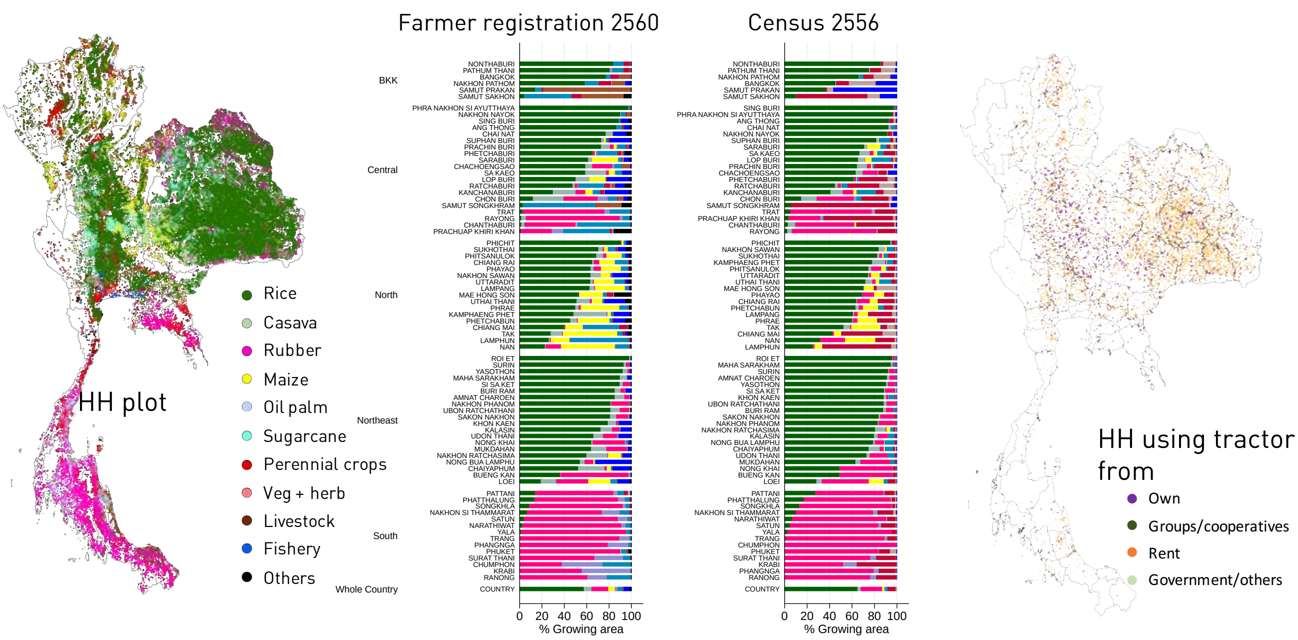
Data source: Census 2546, 2556

Figure 12: : Variations of the Use of Modern Technology by Farm Size and Activity



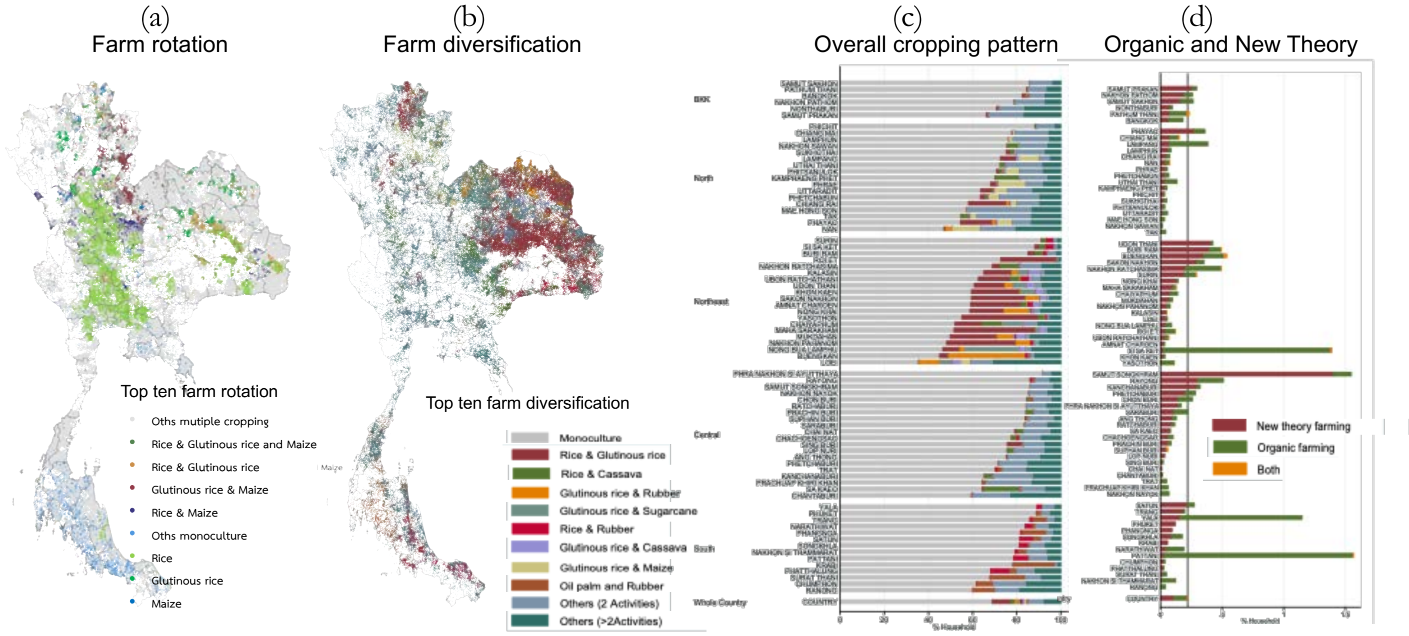
Data source: Census 2556

Figure 13: Variations of Farming Patterns and Emergence of Rental Market



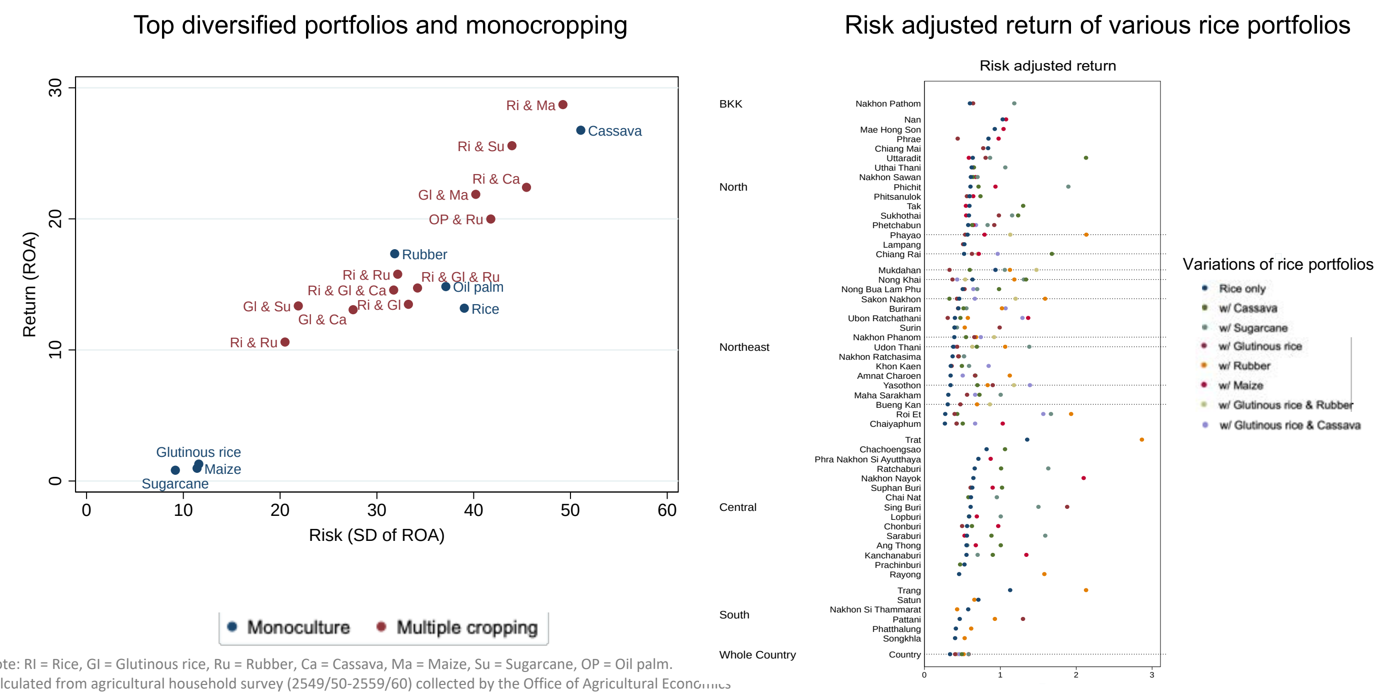
Data source: Farmer registration 2560, Census 2556

Figure 14: Household's Farming Portfolio



Data source: Farmer registration 2560

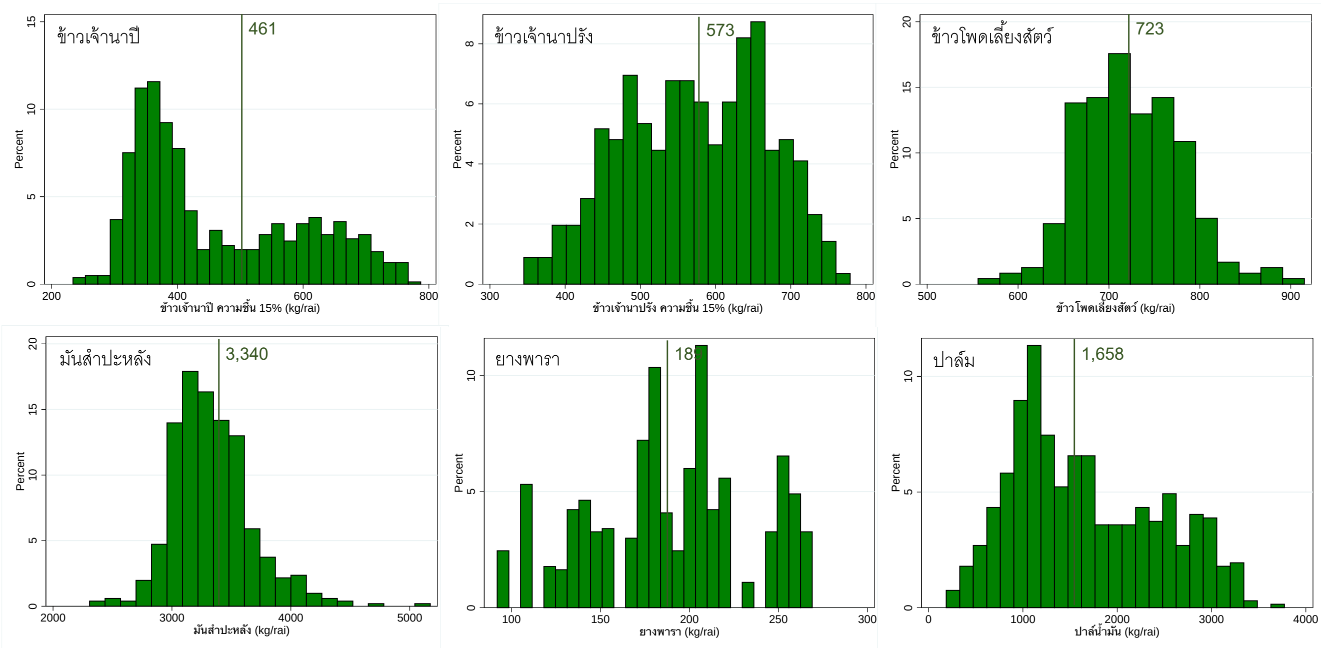
Figure 15: Risk and Return of Farming Portfolios



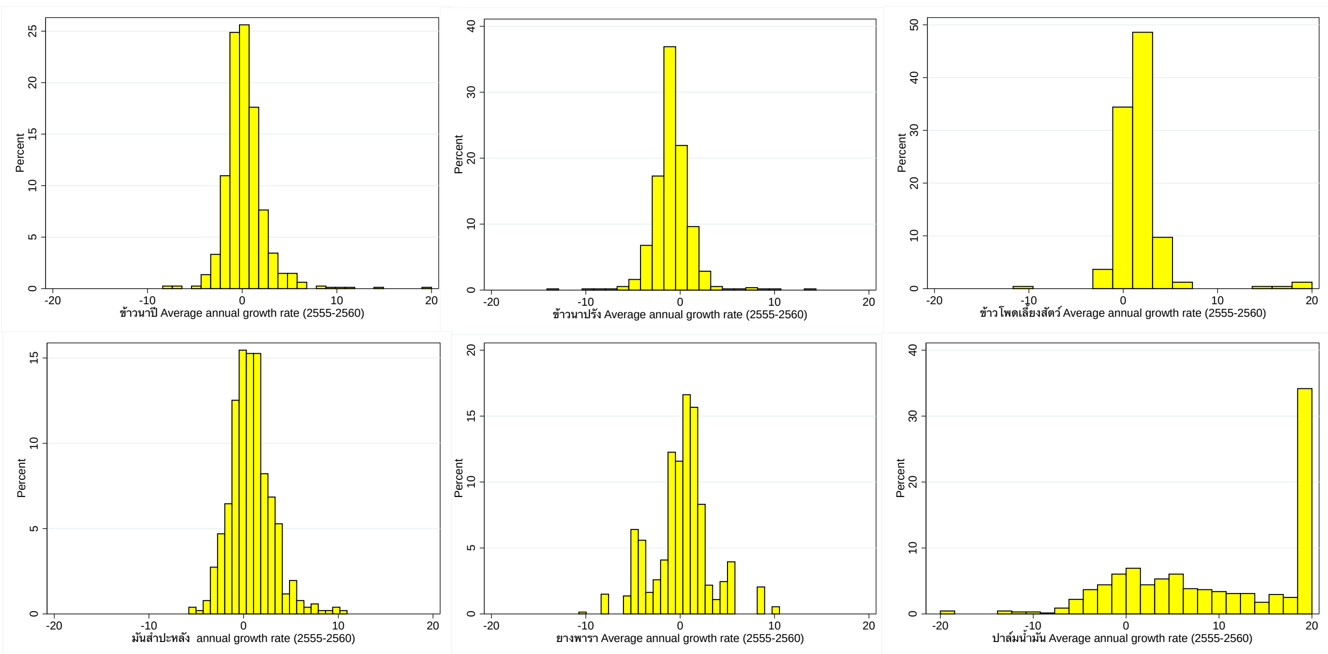
Data source: Agricultural household survey 2549-2560

Figure 16: Variations of productivity of key crops (2561)

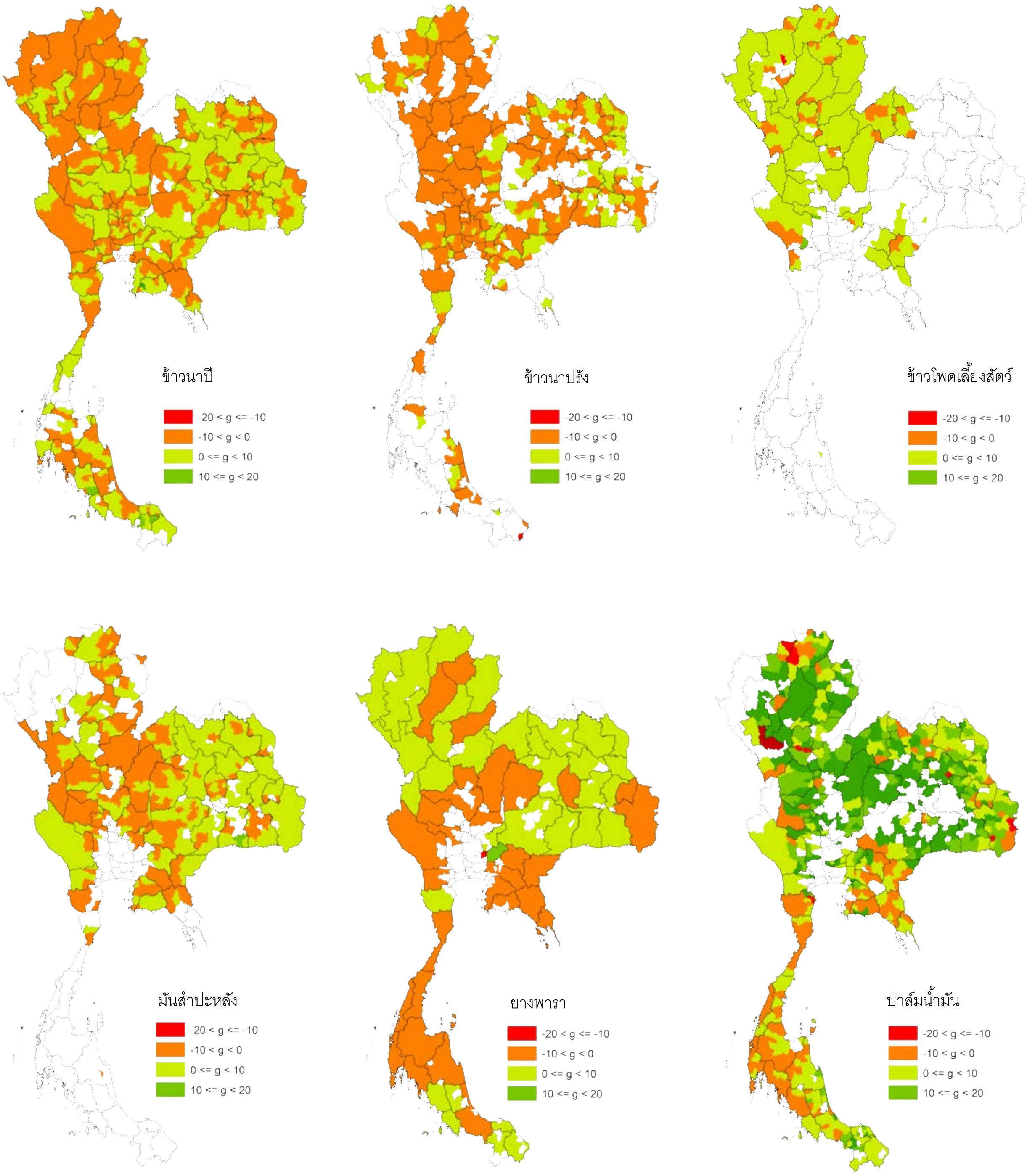
(a) Variations of productivity of key crops (2561)



(b) Variations of productivity growth of key crops (2555-61)

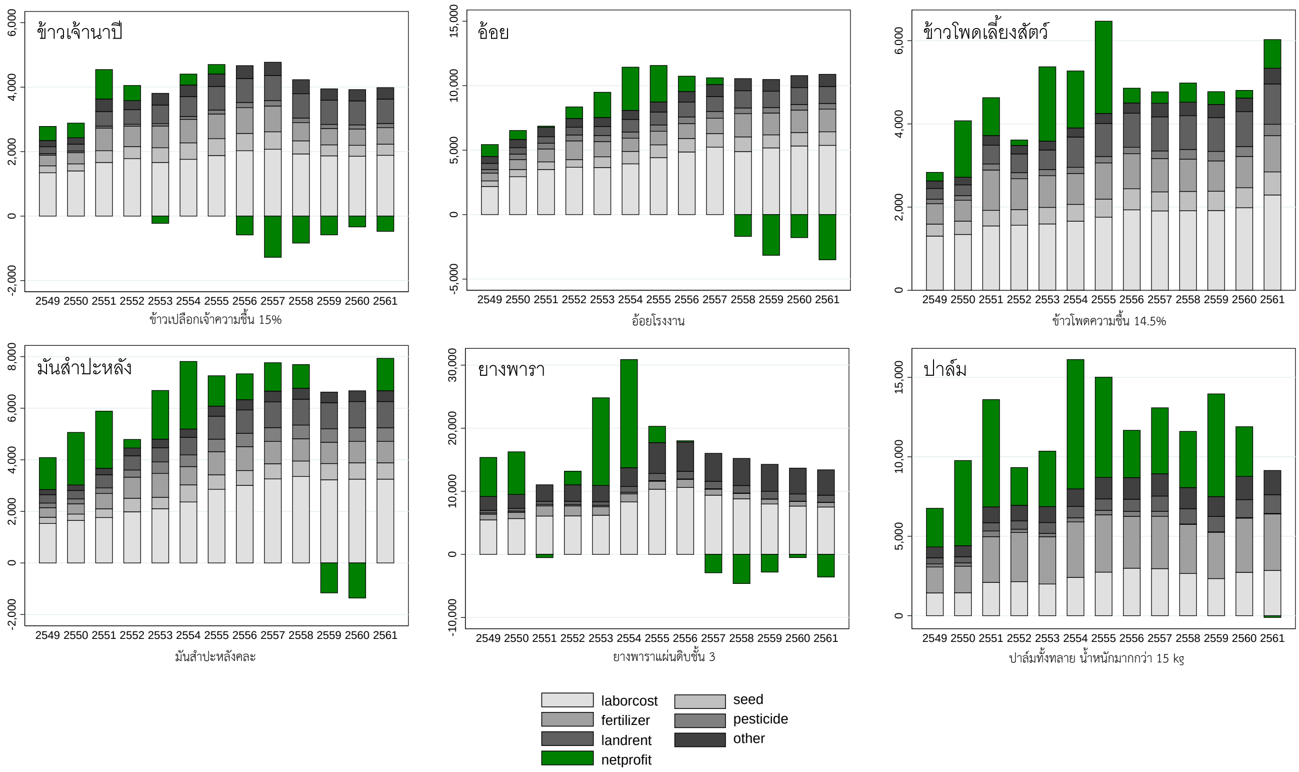


(c) Geographical variations in productivity growth (2555-61)



Data source: Office of Agricultural Economics

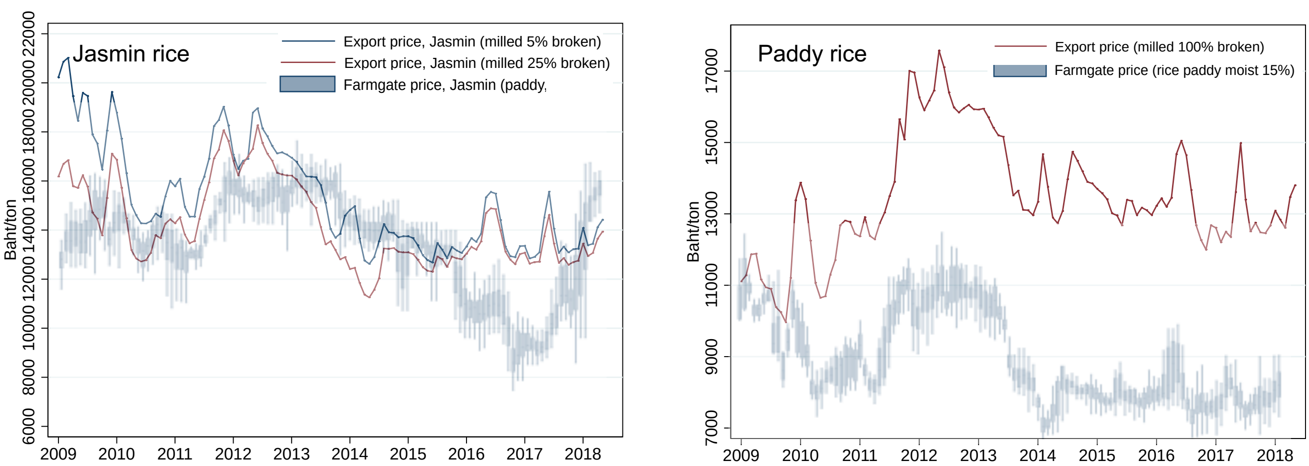
Figure 17: Dynamics of Revenue and Cost Structure (2549-2561)

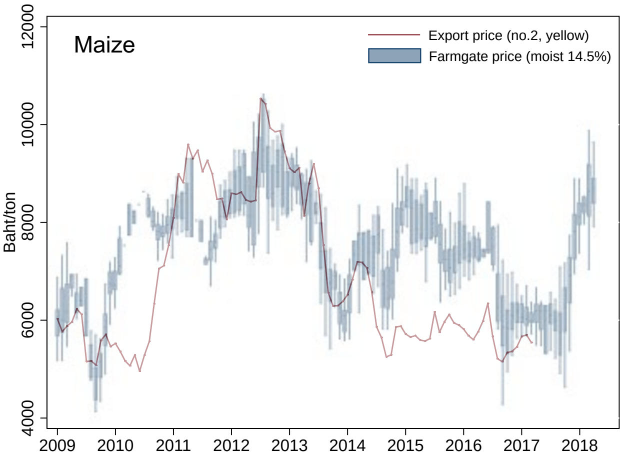


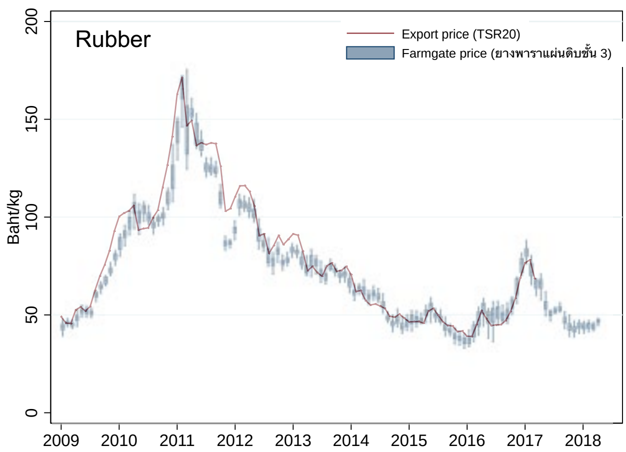
Data source: Office of Agricultural Economics

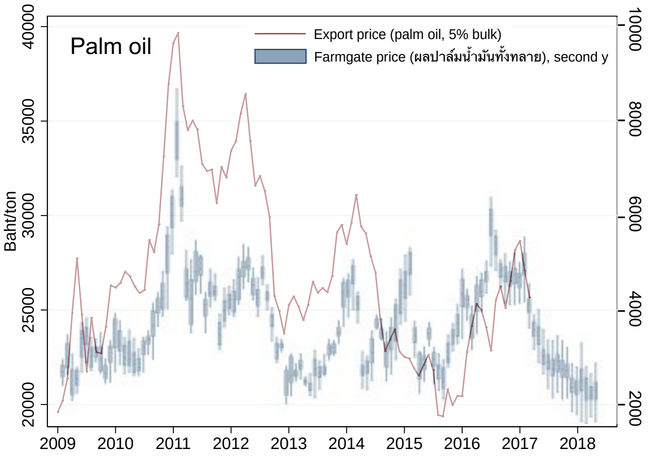
Figure 18: Price Transmission and market structure in agricultural output markets

(a) Export vs. farmgate prices of key commodities

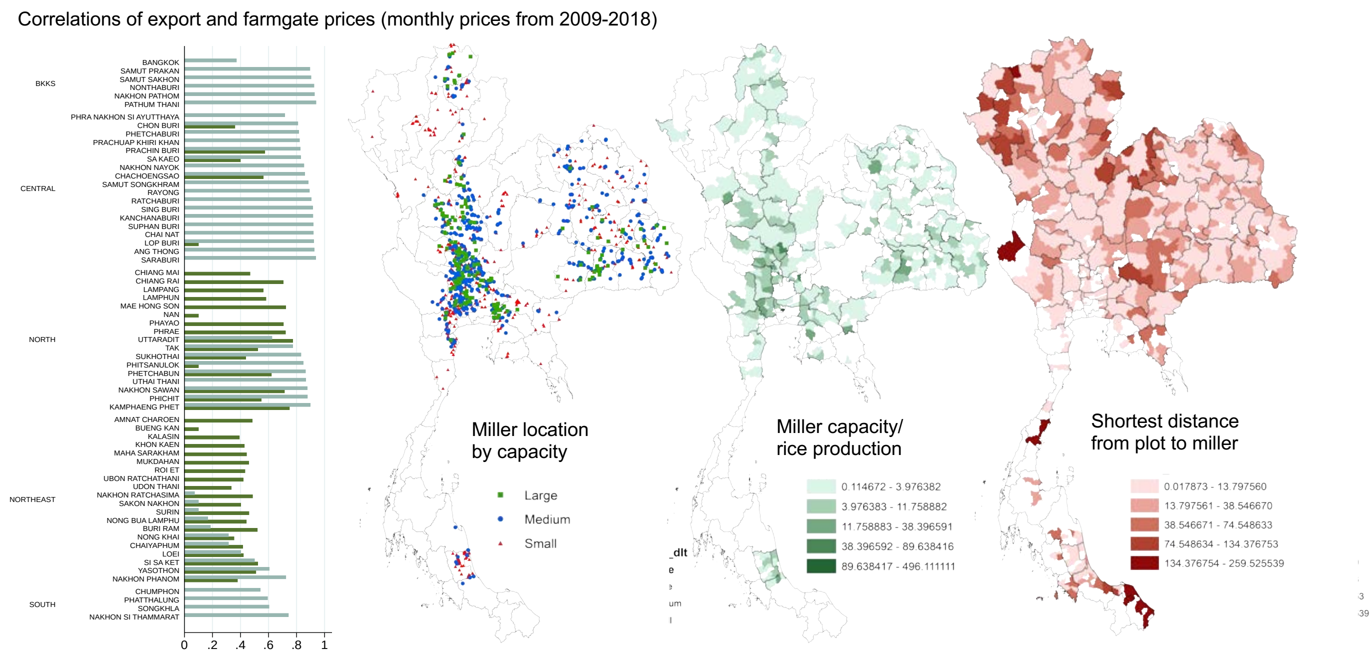






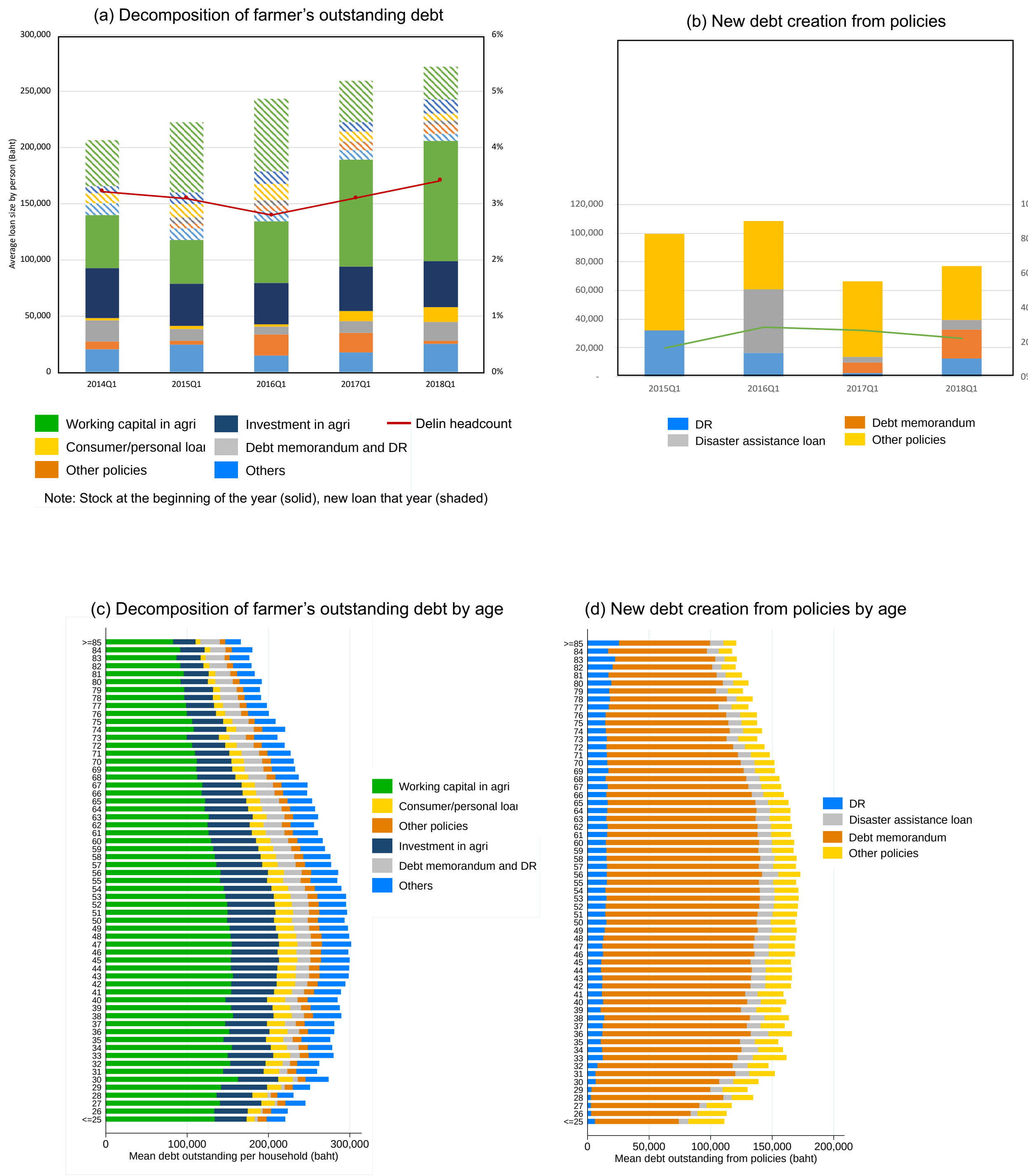


(b) Variations in price transmission in rice markets and distribution of millers



Data sources: Export prices from World Bank Commodity Data, farmgate prices from Office of Agricultural Economics and Miller distribution from AgriMap

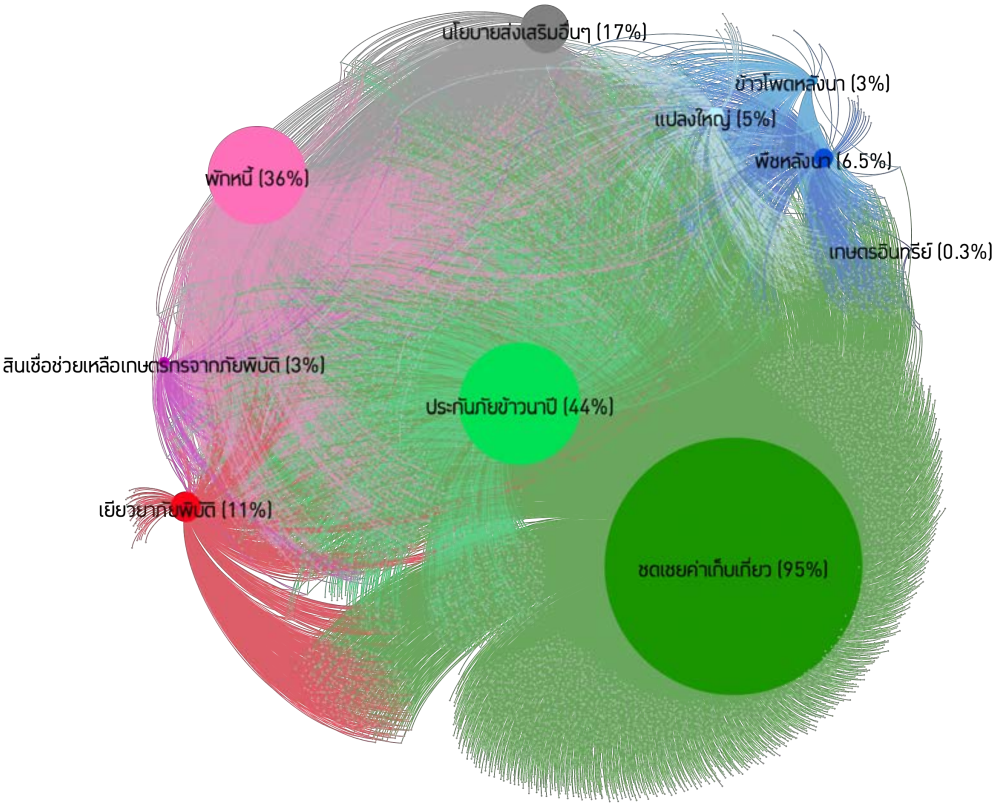
Figure 19: Debt accumulation patterns of Thai farmers



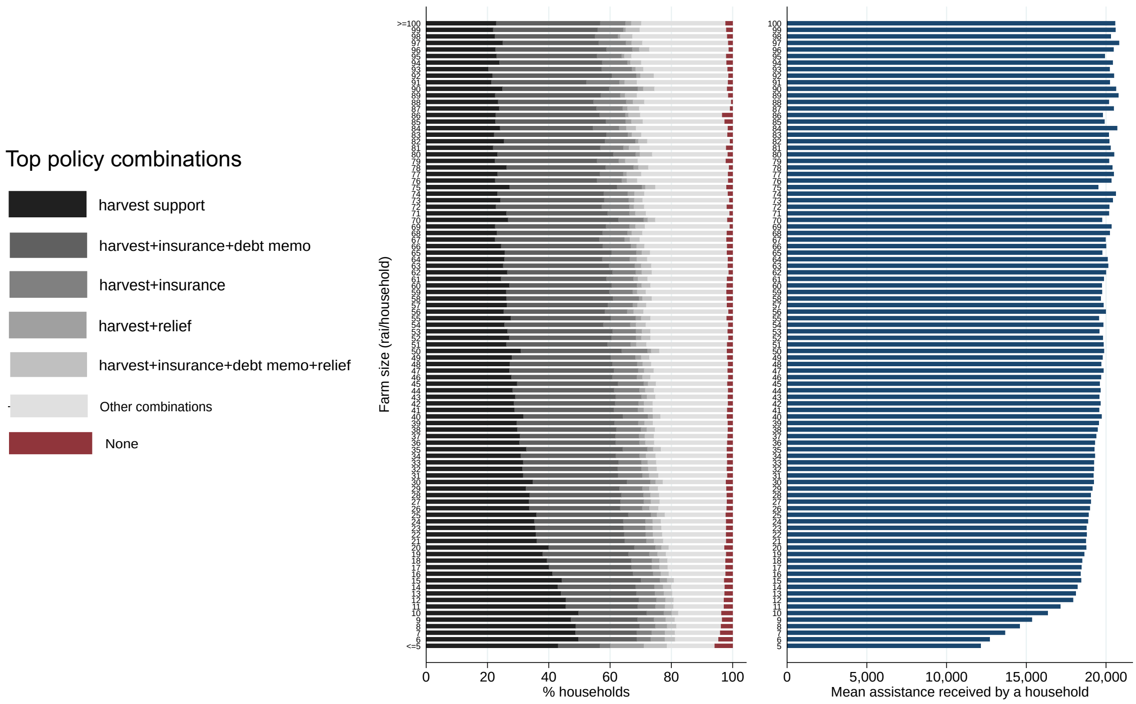
Data source: Loan portfolio of sampled households from Bank of Agriculture and Agricultural Cooperatives

Figure 20: Landscape of government policies and assistance

(a) Policy participation relationship of every registered rice farmers in Thailand



(b) Policies combination and total policy assistance received by a household by farm size



Data source: Policy participation data from Department of Agricultural Extension

Figure 21: Estimated Technical Efficiencies

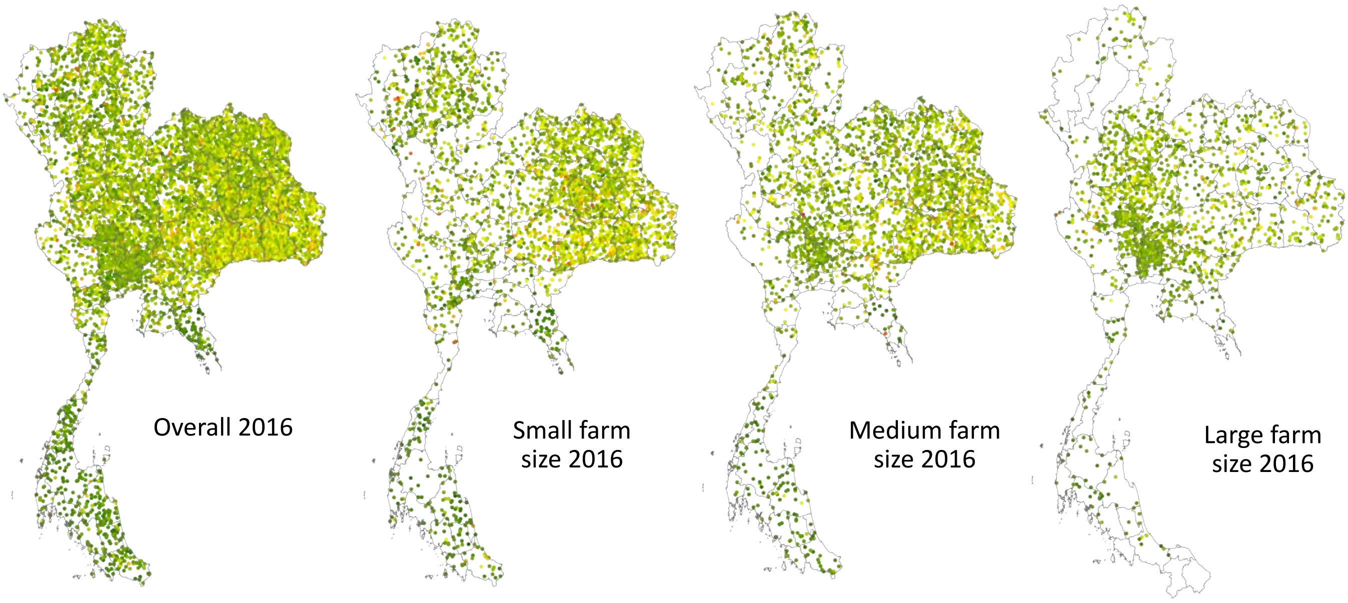


Figure 22: Projected geographical variations in productivity impacts

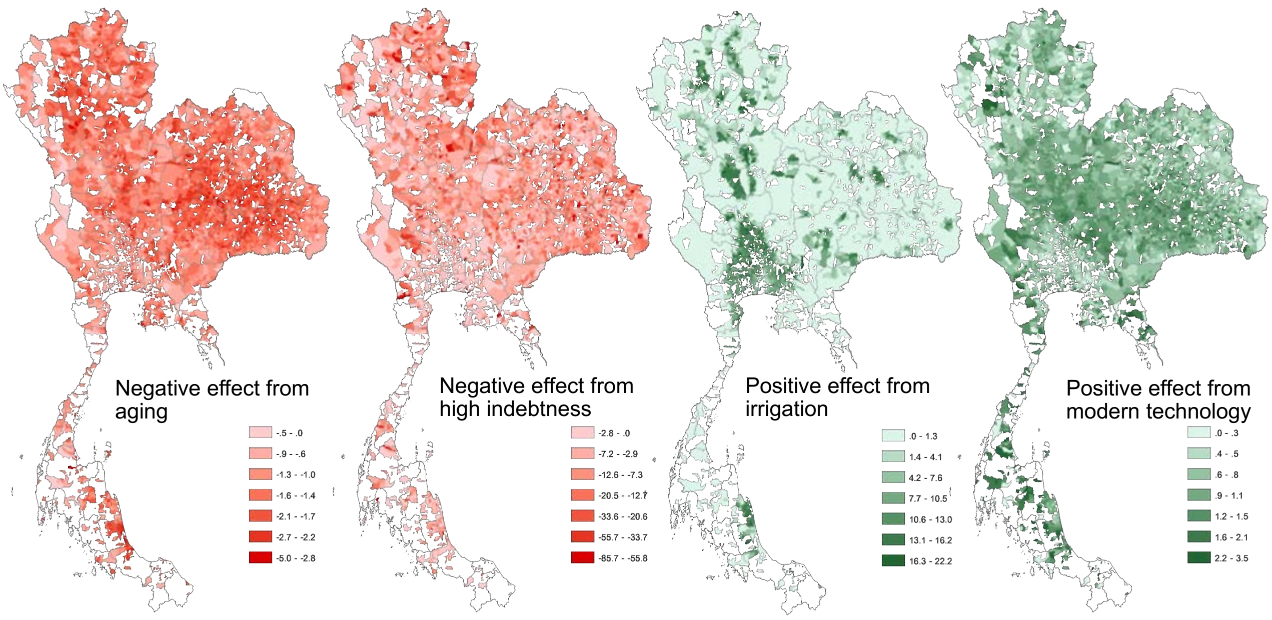


Figure 23: Projected potential productivity impacts of climate change

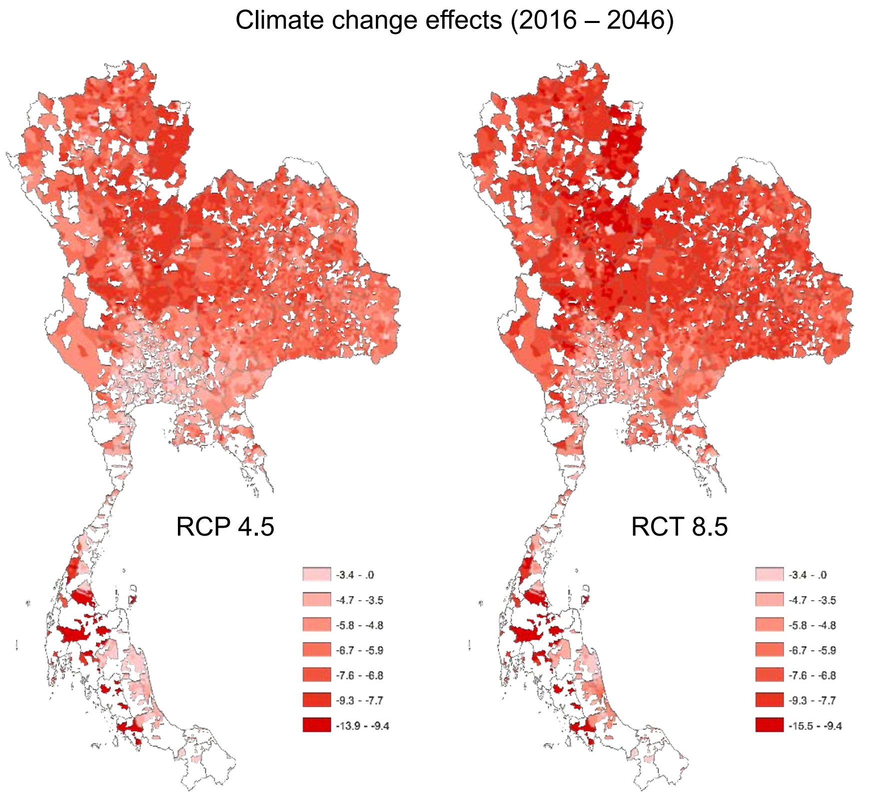


Figure 24: Conceptual Framework for Meta-Analysis

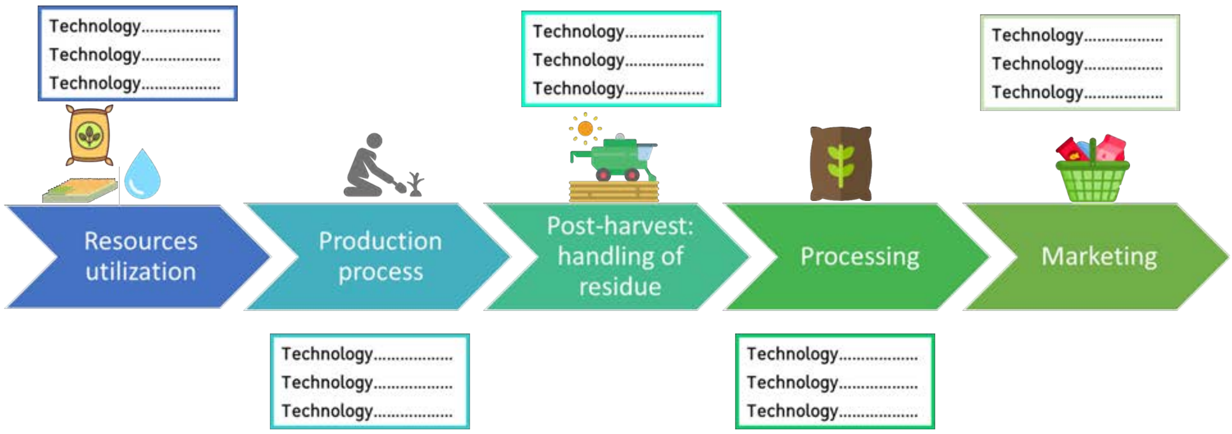
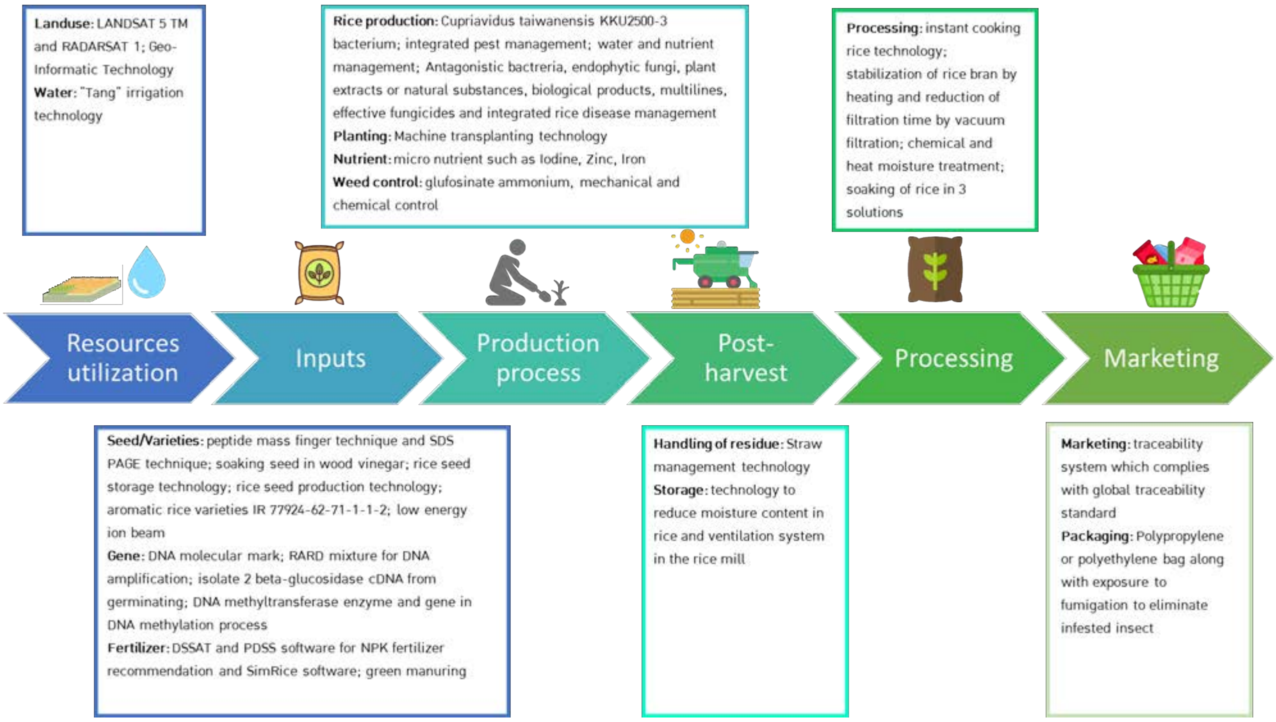
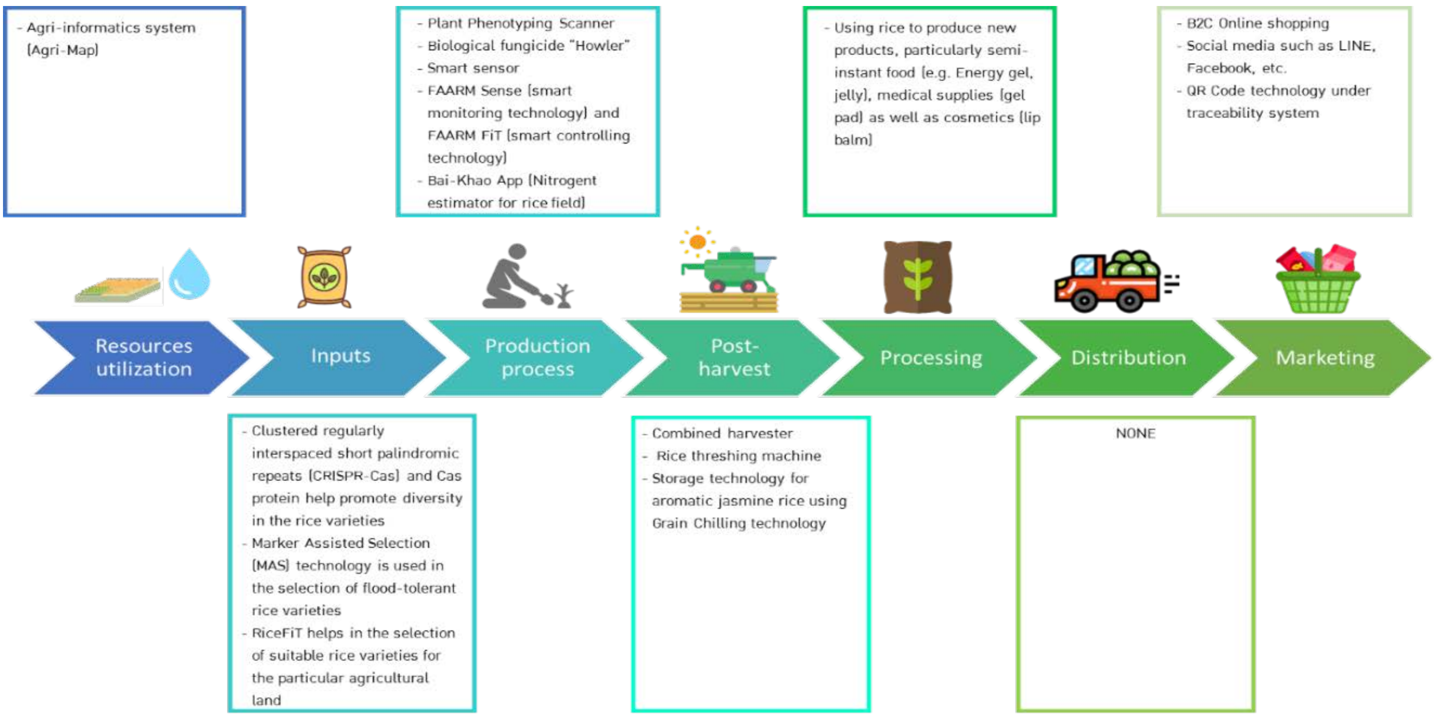


Figure 25: Landscape of Technologies in the Rice Value Chain – TRF and NRCT Database



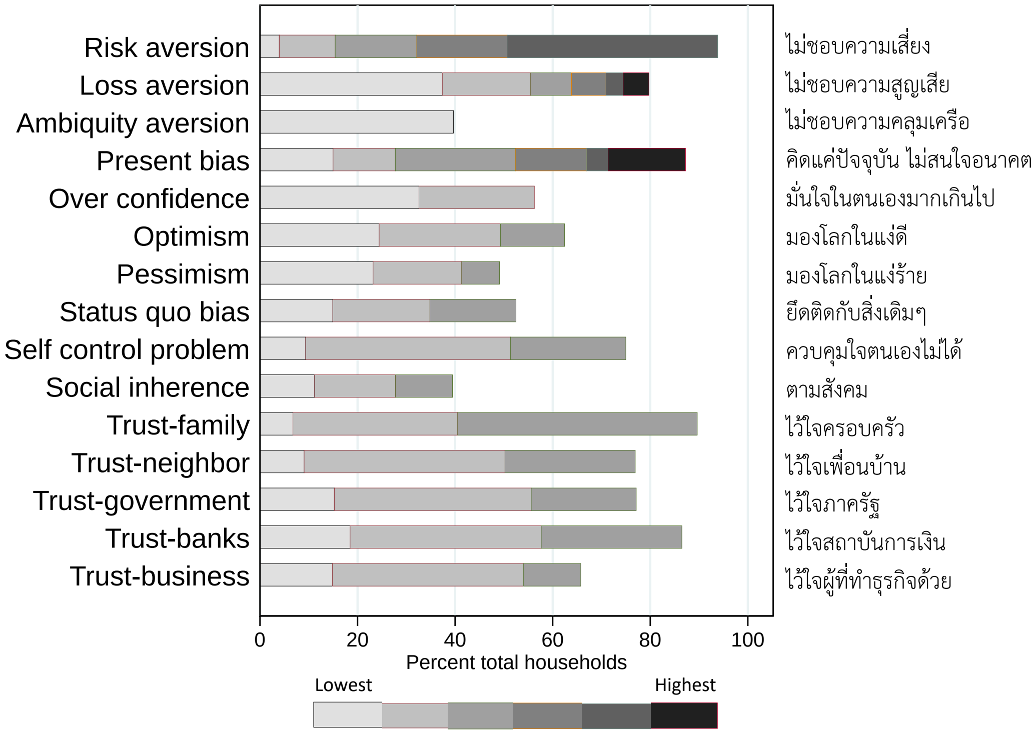
Source: Data from the TRF e-library and NRCT online database; synthesized by Thailand Development Research Institute

Figure 26: Landscape of Existing Technologies in the Rice Value Chain



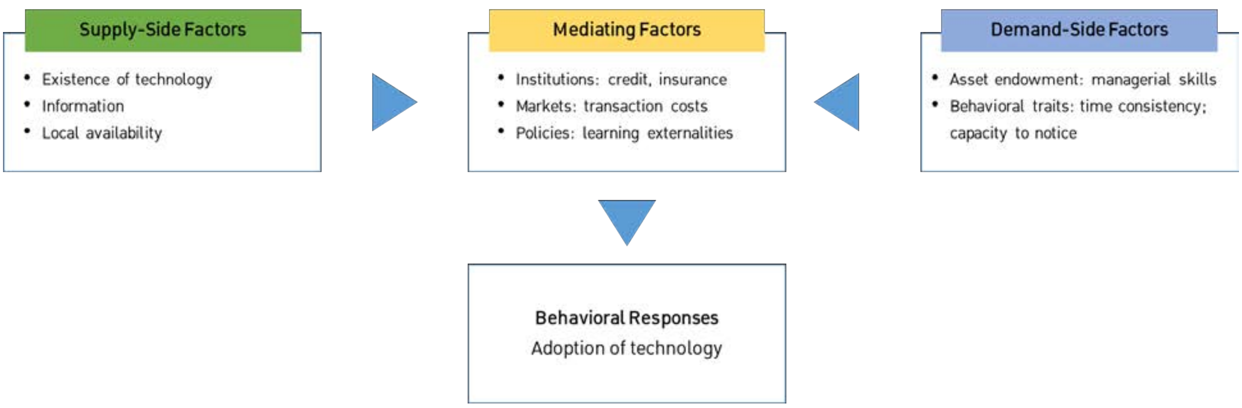
Source: Compiled by Thailand Development Research Institute

Figure 27: Farmer's behavioral biases



Source: Chantarat et al. (2019)

Figure 28: Factors behind the lack of adoption of agricultural technology



Source: De Janvry et al. (2016b)

Figure 29: Treatment arms

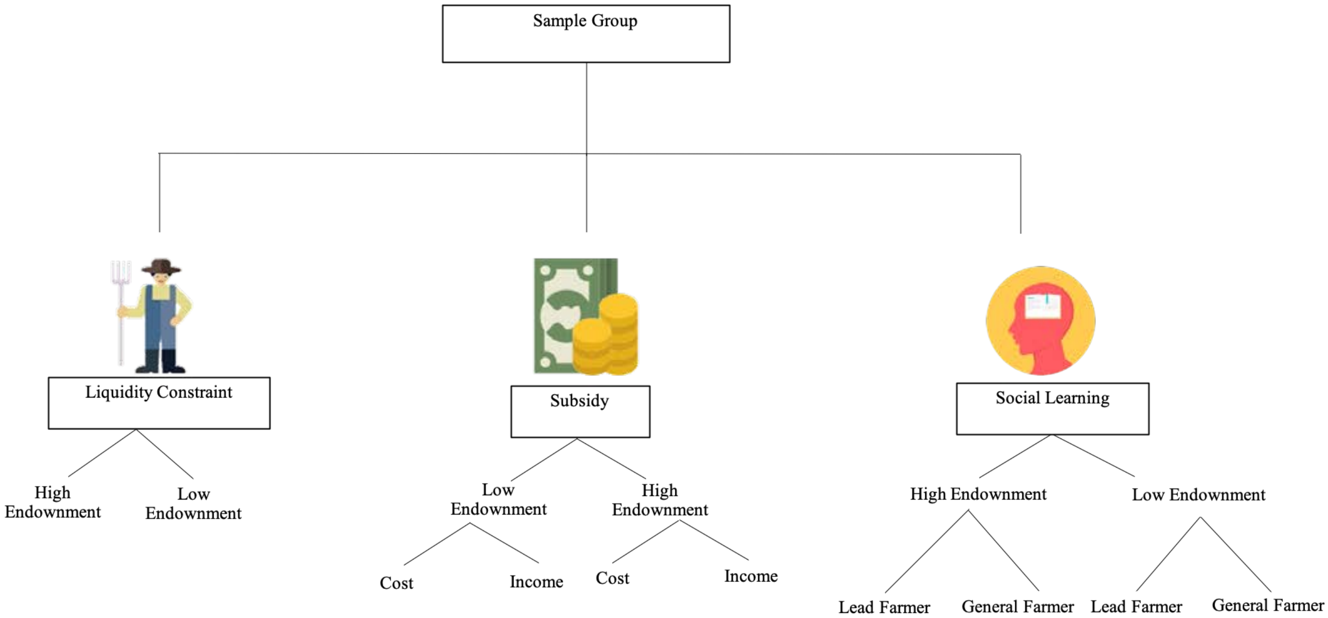
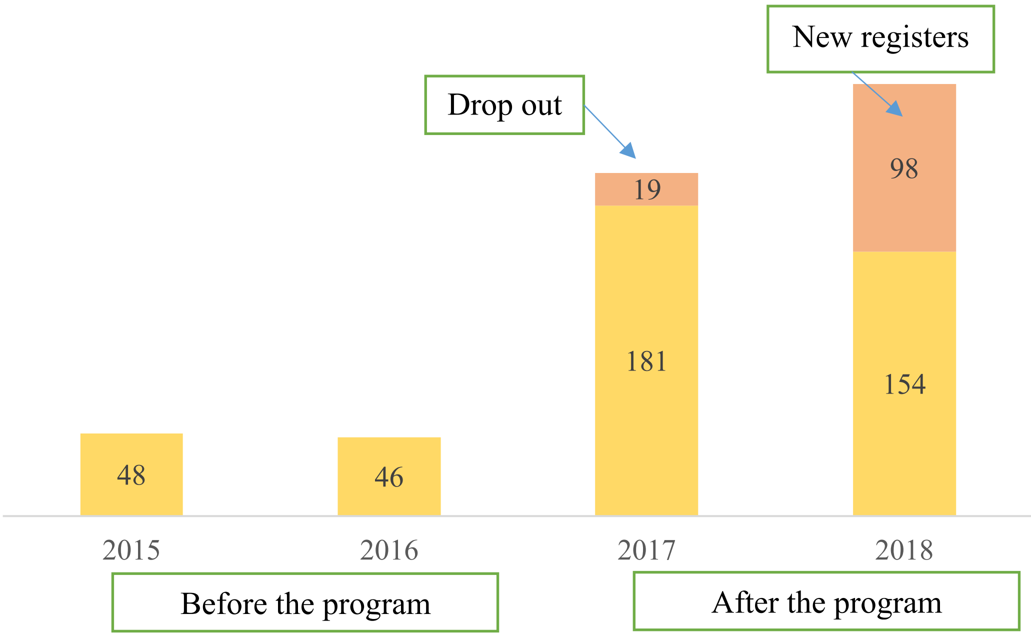
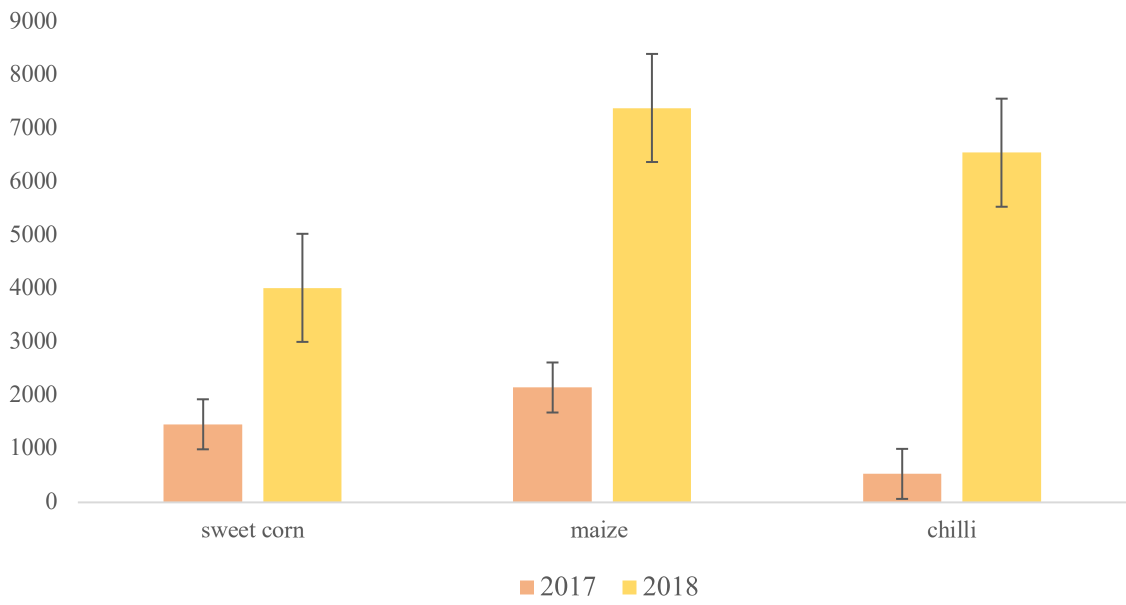


Figure 30: Number of farmers joining the program before and after implementing the risk transfer mechanism.



Source: Mahasuweerachai et al. (2018)

Figure 31: Average profits of the new crops per household between 2017 and 2018.



Source: Mahasuweerachai et al. (2018)

Table 1: Main Sources of Data

Data	Year	Households	Individuals	Plots
1. Farmer registration (DOAE)	2558-2561	5,760,702	15,645,003	12,803,520
2. Agriculture census (NSO)	2546, 2556	5,911,567	19,678,956	10,689,803
3. Agricultural household survey (OAE)	2549-2561	6,997	27,003	26,107
4. Policy participation (DOAE)	2561	3,249,795	-	-
5. Agricultural productivity and prices (OAE)	2555-2561	-	-	-
6. Loan portfolio of sampled farmers (BAAC)	2555-2561	-	1,000,000	-

*Note: Statistics for the latest year of data

Table 2: Regression Results

	(1) Country		Standard errors
ln(output)			
ln(Capital)	0.0167	***	(0.0026)
ln(Labor)	0.1190	***	(0.0020)
ln(Land)	0.4453	***	(0.0049)
ln(Materials)	0.3713	***	(0.0034)
Constant	5.5502	***	(0.0356)
Noise			
Constant	5.5785	***	(0.0360)
Inefficiency			
Ratio of aged farmers	0.1971	***	(5.2700)
Ratio of debt service	0.0293	***	(0.0085)
Yearly maximum temperature	0.1608	***	(0.0123)
24-hr maximum rainfall	0.0076	***	(0.0010)
Oury index shock	0.0817	***	(0.0089)
Oury index	-0.0218	***	(0.0053
Irrigation dummy	-0.6158	***	(0.0355)
Ratio of modern machines and equipments	-0.1008	*	(0.0521)
Constant	-7.8695	***	(0.5542)
Year-fixed effects	Yes		
No. of observations	62,669		

Notes: *** Significant at the 1 percent level, ** 5 percent level and * 10 percent level

Table 3: Positioning of Technology along the Rice Value Chain – TRF Database

Position in the Value Chain	Frequency	Percentage
Damages of rice production	2	8%
Harvest and Storage	3	12%
Inputs	7	28%
Marketing	1	4%
Quality control; rice outputs	4	16%
Rice processing (value-added)	3	12%
Rice production	4	16%
Throughout value chain	1	4%
Grand Total	**25**	**100%**

Source: Data from the TRF e-library; synthesized by Thailand Development Research Institute

Table 4: Types of Rice Technology – TRF Database

Type of Technology	Frequency	Percentage
Climate data and crop modelling	1	4%
Fertilizer recommendation technology	1	4%
Geo-Informatic technology for land use planning for rice production	1	4%
Information technology	1	4%
Packaging technology	1	4%
Post-harvest technology	1	4%
Processing technology	7	28%
Quality control technology	1	4%
Rice gene expression technology	2	8%
Rice planting technology	1	4%
Seed improvement technology	2	8%
Soil improvement technology and weed control technology	1	4%
Storage technology	2	8%
Technology and insurance	2	8%
Weed control technology	1	4%
Grand Total	**25**	**100%**

Source: Data from the TRF e-library; synthesized by Thailand Development Research Institute

Table 5: Positioning of Technology along the Rice Value Chain – NRCT Database

Position in the Value Chain	Frequency	Percentage
Inputs	7	44%
Marketing	1	6%
Resources utilization	2	13%
Rice processing (value-added)	1	6%
Rice production	4	25%
Throughout value chain	1	6%
Grand Total	**16**	**100%**

Source: Data from the NRCT; synthesized by Thailand Development Research Institute

Table 6: Types of Rice Technology – NRCT Database

Types of Technology	Frequency	Percentage
Biotechnology	1	6%
Gene expression technology	2	13%
Information technology	1	6%
Irrigation technology	1	6%
Land preparation, fertilizer management, planting, and harvest technology	1	6%
Pest control technology	1	6%
Processing technology	1	6%
Rice planting technology	1	6%
Rice straw technology	1	6%
Seed improvement technology	5	31%
Traceability technology	1	6%
Grand Total	**16**	**100%**

Source: Data from the NRCT; synthesized by Thailand Development Research Institute

Table 7: Investment, Payoffs and Risks of Crop Failure (unit: THB/rai)

	Investment (THB/rai)	Payoff (THB/rai)	Risk of Crop Failure
Conventional practice (Crop 1)	4	8	20%
New practice (Crop 2)	5	12	50%

Table 8: Full comparison model

Variables	Full comparison
Liquidity constraint	
Low endowment	1.227
	(0.889)
Social learning	
Low endowment_GF	-0.922
	(0.902)
Low endowment_LF	-1.949**
	(0.903)
High endowment_GF	-1.112
	(0.907)
High endowment_LF	-0.265
	(0.911)
Subsidy	
Low endowment_Cost	1.642*
	(0.889)
Low endowment_Income	1.873**
	(0.891)
High endowment_Cost	1.689*
	(0.894)
High endowment_Income	-0.158
	(0.904)
Region	-0.531
	(0.401)
Constant	1.306**
	(0.666)
Observations	4,010
Number of individuals	401

Note: Standard errors are in parentheses. ***, **, and * indicate significant levels at 1%, 5%, and 10%, respectively.

Table 9: Social learning to the new practice adoption

Variables	Full model	Low endowment	High endowment	GF	LF
Low endowment_GF	-0.693	1.103		0.17	
	(0.982)	(0.975)		(1.143)	
Low endowment_LF	-1.728*				-1.591*
	(0.989)				(0.881)
High endowment_GF	-0.867				
	(0.984)				
High endowment_LF			0.810		
			(0.937)		
Region	0.819	-0.919	2.518***	1.892	0.082
	(0.696)	(0.972)	(0.958)	(1.168)	(0.873)
Constant	0.372	-0.542	-1.320	-1.080	0.709
	(0.789)	(0.853)	(0.815)	(1.00)	(0.769)
Observations	1,600	810	790	810	790
Number of individuals	160	81	79	81	79

Note: Standard errors are in parentheses. ***, **, and * indicate significant levels at 1%, 5%, and 10%, respectively.

Table 10: Subsidies to the new practice adoption

Variables	Full model	Low endowment	High endowment	Cost	Income
Low endowment_Cost	1.570**			0.013	
	(0.774)			(0.667)	
Low endowment_Income	1.780**	0.147			1.978**
	(0.776)	(0.772)			(0.882)
High endowment_Cost	1.582**		1.601**		
	(0.77)		(0.747)		
Region	-1.308**	-3.522***	0.808	-1.772***	-0.748
	(0.551)	(0.832)	(0.741)	(0.683)	(0.877)
Constant	1.469**	4.262***	0.329	3.052***	1.246
	(0.617)	(0.773)	(0.651)	(0.613)	(0.78)
Observations	1,600	800	800	800	800
Number of individuals	160	80	80	80	80

Note: Standard errors are in parentheses. ***, **, and * indicate significant levels at 1%, 5%, and 10%, respectively.

Appendix 1: Survey of behavioral bias

1.1 หากท่านได้สิทธิ์ในการเสี่ยงโชคเพื่อรับเงินด้วยการโยนเหรียญ ถ้าออกหัวจะได้เงิน 10,000 บาท ถ้าออกก้อย จะไม่ได้เงิน ท่านจะเลือกทางไหนระหว่าง		
1.1.1	☐ เสี่ยงโยนเหรียญ: ออกหัวได้เงิน 10,000 บาท ออกก้อยไม่ได้เงิน	☐ ได้เงิน 8,000 บาท แน่นอน
1.1.2	☐ เสี่ยงโยนเหรียญ: ออกหัวได้เงิน 10,000 บาท ออกก้อยไม่ได้เงิน	☐ ได้เงิน 6,000 บาท แน่นอน
1.1.3	☐ เสี่ยงโยนเหรียญ: ออกหัวได้เงิน 10,000 บาท ออกก้อยไม่ได้เงิน	☐ ได้เงิน 4,000 บาท แน่นอน
1.1.4	☐ เสี่ยงโยนเหรียญ: ออกหัวได้เงิน 10,000 บาท ออกก้อยไม่ได้เงิน	☐ ได้เงิน 3,000 บาท แน่นอน
1.1.5	☐ เสี่ยงโยนเหรียญ: ออกหัวได้เงิน 10,000 บาท ออกก้อยไม่ได้เงิน	☐ ได้เงิน 2,000 บาท แน่นอน

1.2 หากท่านพาเพื่อนไปเลี้ยงโต๊ะจีน เจ้าของร้านใจดีให้ท่านเลือก ท่านจะเลือกทางไหนระหว่าง		
1.2.1	☐ เสี่ยงโยนเหรียญ: ออกหัวเสียเงิน 10,000 บาท ออกก้อยไม่เสียเงิน	☐ เสียเงิน 2,000 บาท แน่นอน
1.2.2	☐ เสี่ยงโยนเหรียญ: ออกหัวเสียเงิน 10,000 บาท ออกก้อยไม่เสียเงิน	☐ เสียเงิน 3,000 บาท แน่นอน
1.2.3	☐ เสี่ยงโยนเหรียญ: ออกหัวเสียเงิน 10,000 บาท ออกก้อยไม่เสียเงิน	☐ เสียเงิน 4,000 บาท แน่นอน
1.2.4	☐ เสี่ยงโยนเหรียญ: ออกหัวเสียเงิน 10,000 บาท ออกก้อยไม่เสียเงิน	☐ เสียเงิน 6,000 บาท แน่นอน
1.2.5	☐ เสี่ยงโยนเหรียญ: ออกหัวเสียเงิน 10,000 บาท ออกก้อยไม่เสียเงิน	☐ เสียเงิน 8,000 บาท แน่นอน

1.3 หากท่านจะขายข้าวให้โรงสี โรงสีจะรับซื้อข้าวท่านจำนวน 10,000 บาทในอีก 6 เดือนข้างหน้า แต่โรงสีเปลี่ยนใจกลับมาบอกท่านว่าเอามาขายวันนี้ก็ได้ แต่ได้น้อยกว่า 10,000 บาท ท่านจะเลือกทางไหนระหว่าง		
1.4.1	☐ รับเงิน 9,400 บาท วันนี้	☐ รอรับเงิน 10,000 บาท ในอีก 6 เดือนข้างหน้า
1.4.2	☐ รับเงิน 8,800 บาท วันนี้	☐ รอรับเงิน 10,000 บาท ในอีก 6 เดือนข้างหน้า
1.4.3	☐ รับเงิน 8,200 บาท วันนี้	☐ รอรับเงิน 10,000 บาท ในอีก 6 เดือนข้างหน้า
1.4.4	☐ รับเงิน 7,500 บาท วันนี้	☐ รอรับเงิน 10,000 บาท ในอีก 6 เดือนข้างหน้า
1.4.5	☐ รับเงิน 6,300 บาท วันนี้	☐ รอรับเงิน 10,000 บาท ในอีก 6 เดือนข้างหน้า
1.4.6	☐ รับเงิน 5,000 บาท วันนี้	☐ รอรับเงิน 10,000 บาท ในอีก 6 เดือนข้างหน้า

1.4 หากท่านจะขายข้าวให้โรงสี โรงสีจะรับซื้อข้าวท่านจำนวน 10,000 บาทในอีก 1 เดือนข้างหน้า แต่โรงสีเปลี่ยนใจกลับมาบอกท่านว่าเอามาขายวันนี้ก็ได้ แต่ได้น้อยกว่า 10,000 บาท ท่านจะเลือกทางไหนระหว่าง		
1.3.1	☐ รับเงิน 9,400 บาท วันนี้	☐ รอรับเงิน 10,000 บาท ในอีก 1 เดือนข้างหน้า
1.3.2	☐ รับเงิน 8,800 บาท วันนี้	☐ รอรับเงิน 10,000 บาท ในอีก 1 เดือนข้างหน้า
1.3.3	☐ รับเงิน 8,200 บาท วันนี้	☐ รอรับเงิน 10,000 บาท ในอีก 1 เดือนข้างหน้า
1.3.4	☐ รับเงิน 7,500 บาท วันนี้	☐ รอรับเงิน 10,000 บาท ในอีก 1 เดือนข้างหน้า
1.3.5	☐ รับเงิน 6,300 บาท วันนี้	☐ รอรับเงิน 10,000 บาท ในอีก 1 เดือนข้างหน้า
1.3.6	☐ รับเงิน 5,000 บาท วันนี้	☐ รอรับเงิน 10,000 บาท ในอีก 1 เดือนข้างหน้า

1.5 โปรดตอบคำถามต่อไปนี้	
1.5.1 ท่านคิดว่าในโลกนี้มีกี่ประเทศ	☐ 184 ประเทศ ☐ 195 ประเทศ ☐ 217 ประเทศ
1.5.2 ท่านคิดว่าจักรยานยนต์ประดิษฐ์ครั้งแรกเมื่อ พ.ศ. ใด	☐ พ.ศ. 2310 ☐ พ.ศ. 2345 ☐ พ.ศ. 2410
1.5.3 ท่านคิดว่าร้านเซเว่น อีเลฟเว่น สาขาแรกในไทยอยู่ที่ใด	☐ ถนนพัฒน์พงศ์ ☐ ถนนศรีนครินทร์ ☐ ถนนสาทร
1.5.4 ท่านคิดว่าท่านตอบถูกกี่ข้อ	ข้อ
1.5.5 ท่านคิดว่าท่านตอบถูกเป็นอย่างไรเทียบกับคนในห้อง	☐ มากกว่า ☐ น้อยกว่า ☐ เท่ากับ

ต่อไปนี้ ตอบ 1 =ไม่เห็นด้วยอย่างยิ่ง 2=ไม่เห็นด้วย 3= ไม่ทราบ 4=เห็นด้วย 5=เห็นด้วยอย่างยิ่ง

1.6 ท่านเห็นด้วยกับข้อความต่อไปนี้มากน้อยเพียงใด	1	2	3	4	5
1.6.1 หลาย ๆครั้งที่ท่านคิดจะประหยัดเงินแต่สุดท้ายก็อดใจไม่ไหวนำเงินไปซื้อของ					
1.6.2 ท่านเคยตั้งใจจะทำอะไรบางอย่าง เช่น เลิกเหล้า เลิกบุหรี่ ส่วนใหญ่ท่านทำได้					
1.6.3 ท่านมักจะทำอะไรตามเพื่อนบ้านเสมอ หรืออยากมีอะไรตามเพื่อนบ้านเสมอ ๆ					
1.6.4 ท่านเห็นด้วยกับคำพังเพยที่ว่า “มีเงินเรียกน้อง มีทองเรียกพี่”					
1.6.5 เวลาครอบครัวท่านมีปัญหา ท่านมักสามารถพึ่งพาเพื่อนบ้านได้					
1.6.6 เวลาครอบครัวท่านมีปัญหา ท่านมักสามารถพึ่งพาญาติพี่น้องได้					
1.6.7 หากเกิดปัญหาขึ้นทำให้ผลผลิตของท่านเสียหาย ท่านน่าจะพึ่งพิงภาครัฐได้					
1.6.8 ท่านคิดว่าผลิตภัณฑ์ทางการเงินที่ ธกส. แนะนำท่าน น่าจะเป็นสิ่งที่ดีและเหมาะสมกับตัวท่าน					
1.6.9 หากภาครัฐแนะนำให้ท่านลองปลูกข้าวพันธ์ใหม่ ท่านพร้อมที่จะลองปลูก					
1.6.10 หากเพื่อนบ้าน/ญาติแนะนำให้ท่านลองปลูกข้าวพันธ์ใหม่ ท่านจะลองปลูก					
1.6.11 หากโรงสีหรือร้านค้าที่ท่านซื้อปัจจัยการผลิตเป็นประจำ แนะนำให้ท่านลองปลูกข้าวพันธ์ใหม่ ท่านพร้อมที่จะทำตามและลองปลูก					
1.6.12 หากเกิดภัยพิบัติในหมู่บ้านท่าน ท่านมักได้รับผลกระทบมากกว่าคนอื่น ๆ					

1.6.13 ท่านคิดว่าท่านเป็นคนโชคดีกว่าเพื่อน					
1.6.14 ท่านคิดว่าทุกอย่างในชีวิตถูกกำหนดมาแล้ว ท่านเปลี่ยนแปลงได้ยาก					

1.7 ใน 10 ปีที่ผ่านมา ท่านเคยเกิดภัยพิบัติจนทำให้ผลผลิตเสียหายกี่ครั้ง	เสียหายบางส่วน ครั้ง
	เสียหายทั้งหมด ครั้ง
	☐ จำไม่ได้
1.8 อีก 10 ปีที่ข้างหน้า ท่านคิดว่าจะเกิดภัยพิบัติจนทำให้ผลผลิตเสียหายกี่ครั้ง	เสียหายบางส่วน ครั้ง
	เสียหายทั้งหมด ครั้ง
1.9 ใน 10 ปีที่ผ่านมา ท่านเคยถูกหวย	เลขท้าย 2-3 ตัว ครั้ง
	รางวัลใหญ่ (1-5) ครั้ง
	☐ ไม่เล่นหวย
1.10 อีก 10 ปีข้างหน้า ท่านคิดว่าจะถูกหวย	เลขท้าย 2-3 ตัว ครั้ง
	รางวัลใหญ่ (1-5) ครั้ง
1.11 ถ้าเล่นแพ้แล้วเสีย ท่านจะเลือกเล่นถุงไหน	☐ ใส ☐ ขุ่น
1.12 ถ้าเล่นชนะแล้วได้ ท่านจะเลือกเล่นถุงไหน	☐ ใส ☐ ขุ่น