博士論文

Evaluating the Economic Impacts of Agricultural Policy Interventions in the Thai Jasmine Rice Markets

(タイのジャスミン米市場における農業政策介入の経済的影響評価**)**

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Ph.D. Dissertation (2020)

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(タイのジャスミン米市場における農業政策介入の経済的影響評価)

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Abstract

Chapter 1: General introduction

One of the chief concerns of agricultural policymakers in developing countries is the low-income levels of smallholder farmers. This concern is reflected in a global agenda on sustainable development that has set to double the income of smallholder farmers by 2030. This dissertation aims to deepen our understanding of the impact of policy interventions that aim to solve farmers' low-income problems by examining agricultural policy interventions in Thailand. As farmers generate most of their income from farming in developing countries, they may have low income due to low productivity or low price, or both. Since competition in the agricultural market plays a central role in determining prices, farmers may receive a low price because of low market competition. Apart from the competition issue, farmers may receive a low price because they cannot optimize selling time using on-farm storage. This dissertation evaluates the economic impacts of three policy interventions that may increase market competition and may allow farmers to store crops at harvest. The Thai Jasmine rice markets are used as a testing ground because they provide appropriate settings.

Chapter 2: Does oligopsony power matter in price support policy design? Empirical evidence from the Thai Jasmine rice market (*Published in **Agriculture Economics***)

In the oligopsony market, farmers may receive low prices and policy analysis assuming perfect competition can yield serious bias results. In this article, I estimate oligopsony power between processors and farmers and evaluate the welfare impact of the paddy pledging program (PPP), a generous price support program in the Thai Jasmine rice market, with an imperfect competition model. I develop a model that consists of rice supply equation and derived demand equation. I then simultaneously estimate these equations using system estimation methods to recover oligopsony power parameters. Lastly, I use these parameters to assess the welfare impact of the price support program. Using annual panel data running from crop marketing year 2001/02 to 2015/16 and

exploiting the institutional feature of the PPP, I find strong evidence of some oligopsony power, a moderate level of oligopsony price distortion, and a negative relationship between price support and oligopsony power. I also find that the PPP is inefficient but effective in income redistribution. Moreover, the program benefits both farmers and consumers. With better policymaking decisions, the PPP can be efficient by setting a suitable support price. Therefore, my results show that in the case of the Thai Jasmine rice market, the generally accepted "wisdom" about agricultural price support policy does not necessarily hold, and price support can be designed to improve the efficiency of the market.

Chapter 3: The spillover effect of direct competition between marketing cooperatives and private intermediaries: Evidence from the Thai rice value chains (2nd *Revised and Resubmitted (Minor revision) for publication in* ***Food Policy***)

Despite the widespread belief that marketing cooperatives' benefits may extend beyond participating farmers, little is known about the cooperative's effect on nonparticipating farmers. This paper exploits exogenous variation in language spoken at home in Thailand to obtain the instrumental variable estimates of the spillover effect of marketing cooperatives. I hypothesize that farmers who sell rice to private intermediaries in the area where there is direct competition between marketing cooperatives and private intermediaries (treated areas) are likely to receive a higher price than those who sell rice in other areas. Using household-level data of rice farmers in Thailand in the marketing year 2018/19, I find strong evidence that farmers in treated areas receive 10.9% higher prices from private intermediaries than those in comparison areas. My results provide crucial implications for food policy debates regarding the role of marketing cooperatives in agri-food value chains. In particular, evaluating the inclusiveness of marketing cooperatives toward poor farmers should not be limited to sampling and analyzing its members only. Failure to consider the spillover effect could lead to substantial underestimation of the impact of marketing cooperatives on societal welfare.

Chapter 4: The market-level effect of large-scale on-farm storage intervention: Evidence from Thailand (*Submitted for publication in* ***Journal of Development Economics***)

Despite the desire to store grain to ensure household food supplies and future income, many farmers in developing countries are forced to sell their crops immediately after harvest because of technology constraints and credit constraints. This paper evaluates the effect of the change in local supply caused by relaxing credit constraints or on-farm storage intervention on local market prices. Because the change in local supply or on-farm storage under the intervention is not random, I employ two econometric strategies. First, I convert my variables to first differences. I then instrument the differenced on-farm storage quantity under the intervention using 4-year, and 5-year lagged on-farm storage. Using 18 years panel data from 19 provinces in Thailand, my instrumental variable estimates indicate that the decrease in local supply caused by on-farm storage intervention has a significant effect on local rice market price. For example, 20,000 tons decrease in local supply induced by the intervention causes the farm gate price of rice in the main harvesting month to increase by 1.31%. In contrast, I find that the change in local supply caused by the intervention cannot stabilize price inter-seasonally in my setting. My findings provide crucial evidence for policy debates regarding the welfare implications of on-farm storage interventions when delivered on a massive scale.

Chapter 5: General conclusion

My doctoral research aims to deepen our understanding about the effect of policy interventions that aim to solve farmers' low-income problems on the functioning of agricultural markets. Specifically, I evaluate three agricultural policy interventions in Thailand, including price support policy, promoting farmer organizations, and supporting on-farm storage. Overall, I find that it is possible to raise farmers' income through existing interventions to some degree, and the impact assessments of these interventions need to include their spillover effects and market-level effects.

Acknowledgements

This thesis would not have been possible without the selfless support and encouragement of numerous people in my life. I am indescribably indebted to my supervisors, Nobuhiro Suzuki and Takeshi Sato. Their generous mentorship, marvelous flexibility and unbelievable patience have been invaluable to my slow learning process.

Professor Suzuki has been a continual source of inspiration. He is incredibly smart and has supported me in all kinds of ways. His guidance has helped me shape my research agenda and improve my research. He emphasized the importance of reconnecting theory with realities and creating the research that is useful to the real world. I deeply admire him for that. Moreover, he gave me a lot of freedom to experiment with my ideas and patiently listened to me. He also gave me the freedom to join and learn from activities other than my research. I am very grateful for the eye-opening experience of exploring and creating knowledge under his guidance.

Assistant professor Sato has always eager to hear about my research. When I showed him new ideas or work in progress, he would offer me a valuable suggestion. His comments have often led me to see the way to enhance my research. I am also thankful that he was incredibly supportive.

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The financial support from MEXT is also gratefully acknowledged. To the end, I would like to thank my friends, family, labmate, and Kanjana Rotsawat. They have listened to me, cooked with me, talked to me, called me, and visited me. Without them, I would not have been where I am today. Thank you so much.

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Chapter 1 General Introduction

1.1 Motivation and problem setting

One of the chief concerns of agricultural policymakers in developing countries is the low-income levels of smallholder farmers. This concern is reflected in a global agenda on sustainable development that has set to double the income of smallholder farmers by 2030 (United Nations., 2015). Smallholder farmers are often trapped in a vicious cycle of poverty. In 2015, approximately 372 million smallholder farmers were living in extreme poverty, that is, they had income below $1.90 per day (Castaneda Aguilar et al., 2016). This dissertation aims to deepen our understanding of the effect of policy interventions that aim to solve farmers' low-income problems on the functioning of agricultural markets in advanced developing country.

As farmers generate most of their income from farming in developing countries, they may have low income due to low productivity or low price, or both. Since competition in the agricultural market plays a central role in determining prices, farmers may receive a low price because of low market competition. As an illustration, consider a simple agricultural value chain:

[Farmers] ➔ [Intermediaries] ➔ [Consumers]

where farmers sell their crops (input) to intermediaries such as traders and processors, and then intermediaries sell processed crops (output) to consumers. Suppose Figure 1.1 represents the market in this supply chain.

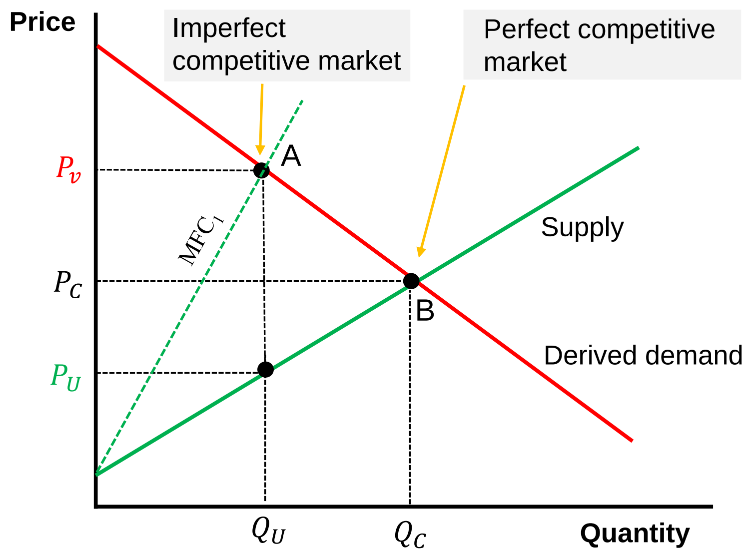

Figure 1.1 Simple model of agricultural market

If the market is perfectly competitive, the intersection of the market demand curve and the market supply curve will determine the competitive equilibrium at B, where intermediaries purchase Q_c unit at price P_c per unit. Economic theory indicates that three conditions are indispensable for the market to be perfectly competitive. First, market agents should be able to enter and exit the market freely. Under this condition, an intermediary cannot maintain its profits by depressing its price paid to farmers below the market price. This is because other intermediaries will enter the market and offer a better price to farmers until the intermediary's profits are driven to zero. Second, market agents must have perfect price information. If farmers know the price offered by intermediaries in other markets, an intermediary cannot depress the price without losing its suppliers. In contrast, if farmers do not know the price offered by intermediaries in other markets, an intermediary can pay farmers lower than other intermediaries without losing all its suppliers. Third, the transaction costs or the expense of finding a trading partner (intermediary) and making a trade for agricultural products must be low. If the transaction costs are low, farmers can quickly and easily sell their crops to a rival intermediary if the farmers' usual buyers depress its buying price. If these three conditions hold, the input market will be perfectly competitive.

However, many of these conditions are unlikely to hold in reality. First, farmers usually lack information about the market price in other markets because of villages' remoteness and the high cost of finding information (Courtois and Subervie, 2015). Second, intermediaries usually lack non-market price information such as crop quality in other markets other than those they usually operate (Arimoto et al., 2018). This situation creates a barrier to entry. Third, the high transportation cost of agricultural products deters farmers from seeking selling opportunities beyond their nearby areas. As a result, farmers have limited selling options. In these settings, the market will be imperfectly competitive. For example, Bergquist and Dinerstein's (2020) recent experimental study shows that maize traders in Kenya do not compete but act as a cartel. When intermediaries do not compete, they will have market power or the ability to set prices in the markets.

If intermediaries exercise buyer market power, farmers will receive a low price. As intermediaries can influence input price due to market power, their marginal factor cost[1] (MFC_I) lies above the linear supply curve. To maximize profit, intermediaries set the marginal factor cost equal to the value of the marginal product[2] (derived demand curve) at A. They will purchase Q_U tons at price P_u[3]. Thus, the intermediaries buy and pay lower than a competitive market would do. As a result, farmers will receive a low price while consumers will pay a high price when the market is imperfectly competitive.

Apart from the competition issue, farmers may receive a low price because they cannot optimize selling time. Generally, farm prices are lowest during the harvesting season when supplies are abundant. However, many smallholder farmers in developing countries are forced to sell at harvest when the prices are low because of credit and liquidity constraints and technology constraints (e.g. Aggarwal et al., 2018; Dillon, 2020; Kadjo et al., 2018; Stephens and Barrett, 2011). As a result, they are forced to forgo many potential benefits from on-farm storage, such as choosing the best selling time. For example, poor farm households in Malawi missed out on an expected 17.3-26.5% increase in crop prices over three months because they are forced to sell crops early to finance their children's education (Dillon, 2020).

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[1] Additional cost of buying one more unit of input

[2] Value of marginal products is a measure of a firm's revenue from adding one more unit of inputs.

[3] At Q_U farmers is willing to sell at a price P_u. Hence, the price that the intermediary pays is found from the supply curve.

This dissertation evaluates the economic effect of three policy interventions that may increase market competition and may allow farmers to store crops at harvest. The Thai Jasmine rice markets are used as a testing ground because they provide appropriate settings. The next section presents background information about Thai Jasmine rice markets and policy interventions in these markets.

1.2 Background

1.2.1 A brief profile of Thailand

Thailand, officially the Kingdom of Thailand, is located in mainland Southeast Asia (Figure 1.2). Thailand's total population in 2019 was 66.56 million. Over the last four decades, Thailand has experienced remarkable progress in economic development, moving from a low-income to an upper middle-income country. Yet, despite all that progress, the country is now trapped in an upper middle-income level. Since 2011, Thailand has been unable to become an advanced country. In recent years, the country has been facing several problems such as political instability, increasing inequality, and weakness in education outcomes (World Bank., 2020a).

Agriculture remains an important sector in the Thai economy. In 2019, the agricultural sector accounted for 31.6% of total employment and 8.0% of gross domestic products or GDP (World Bank., 2020b). The main agricultural products in Thailand are rice, natural rubber, cassava, and sugarcane. Many of these products are traded internationally. In 2019, Thailand was the world's second-largest exporter of rice and sugar and the biggest exporter of natural rubber and cassava (United Nations., 2020). Although Thailand is very successful in exporting agricultural products, 40% of farming households or approximately 2.5 million farm household are still living below the poverty line, set at 9057 yen/per month (Banchongduang, 2018).

Figure 1.2 Map of Thailand

Source: https://legacy.lib.utexas.edu/maps/middle_east_and_asia/thailand_admin-2013.jpg

1.2.2 Overview of Jasmine rice markets

In Thailand, farmers grow various varieties of rice. Figure 1.3 (*left*) shows rice-growing areas in Thailand by type of rice varieties. We could classify different rice varieties into three groups: Non-glutinous rice, Glutinous rice, and Jasmine rice. Non-glutinous rice is grown mostly in the center and northern regions of Thailand. In contrast, Glutinous rice and Jasmine rice are grown mainly in the northeast part of Thailand. In 2017, Non-glutinous rice, Jasmine rice, and Glutinous rice accounted for 43%, 37%, and 20% of total Thai rice production in the main growing season, respectively (Figure 1.3 (*right*)).

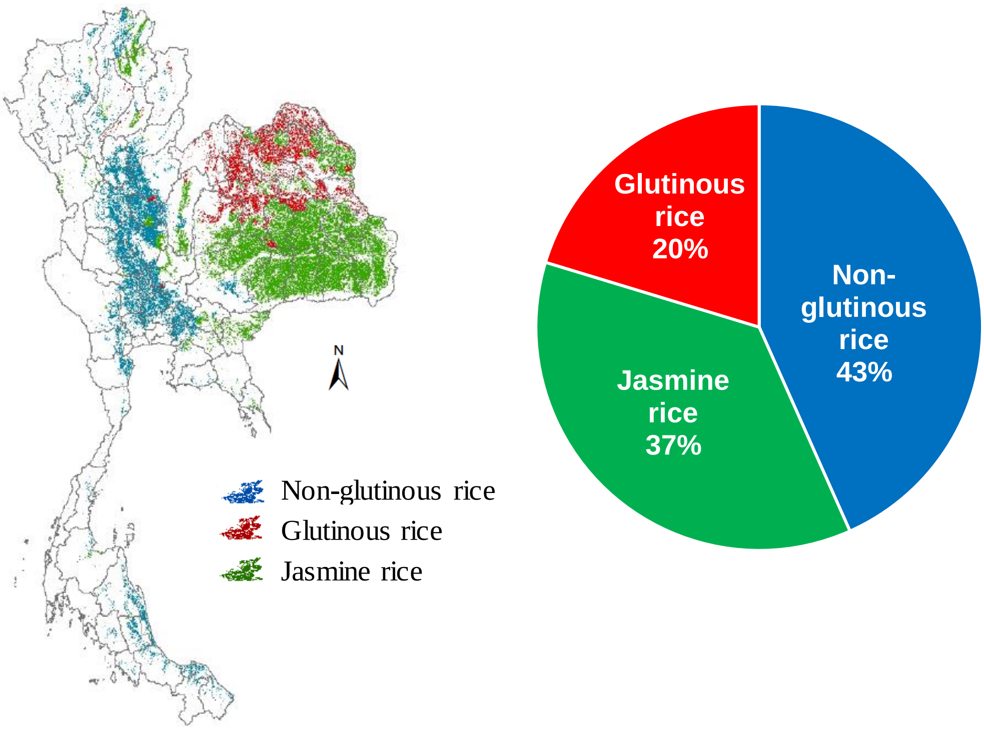

Figure 1.3 *left*, Rice growing area in Thailand by type of rice varieties; *right*, Thai rice production in the main growing season classified by type of rice varieties in 2017
Source: *left*, Thai Rice Foundation (2013); *right*, created by the authors based on data from Office of Agricultural Economics (2017)

Jasmine rice, also known locally as Khao Hom Mali, is grown mostly by the poor. Jasmine rice was an improved rice variety developed by the Bureau of Rice Research and Development in Thailand. It was released to farmers in 1959 (Vanavichit et al., 2018). Due to its remarkable cooking qualities, such as soft-texture and aroma, Jasmine rice has commanded a premium price on domestic and international markets. For example, Jasmine rice's farm gate price in 2019 was $402.3 per ton, while the farm gate price of non-glutinous rice was only $220.1 per ton (Figure 1.4)

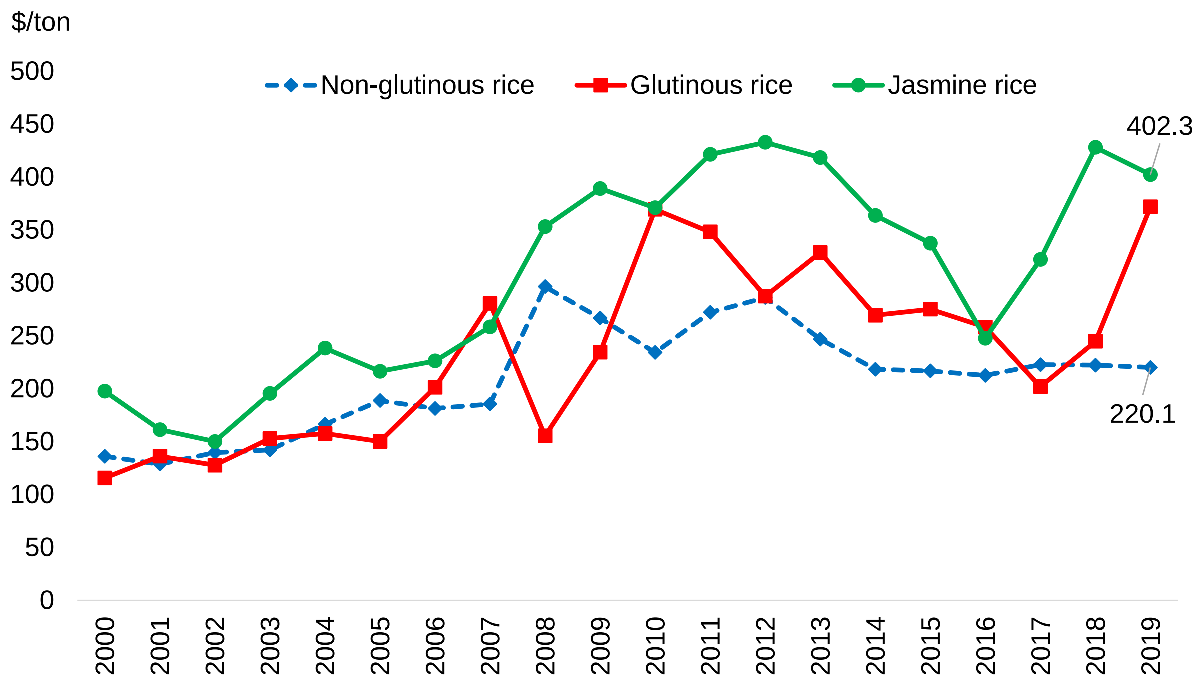

Figure 1.4 Farm gate price by type of rice varieties

Source: Data from Office of Agricultural Economics (2020)

Given its high price, Jasmine rice has been widely adopted by poor farmers. Figure 1.5 shows that the poorest population in Thailand is concentrated where the Jasmine rice is mostly grown. In 2016, approximately 1.9 million households with an average farm size of 2.15 hectares per household grew Jasmine rice. These farmers accounted for 53.0% of total rice farming households in Thailand (Rice Department., 2016).

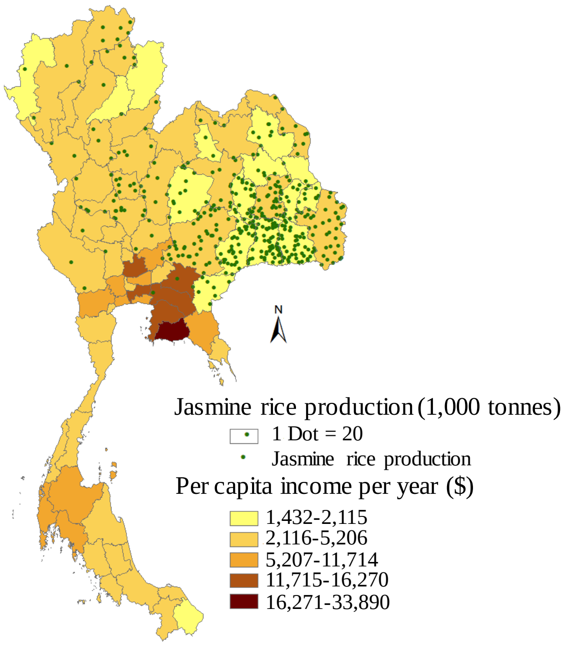

Figure 1.5 Jasmine rice production and per capita income in 2013

Source: Created by the authors based on data from the National Statistical Office of Thailand (2014) and Office of Agricultural Economics (2017).

Figure 1.6 shows that, during the 19 years, the Jasmine rice-growing area increased by approximately 52.4%, from 2.8 million hectares in 2001 to 4.3 million hectares in 2019. In contrast, Non-glutinous rice and Glutinous rice-growing areas decreased during the same period.

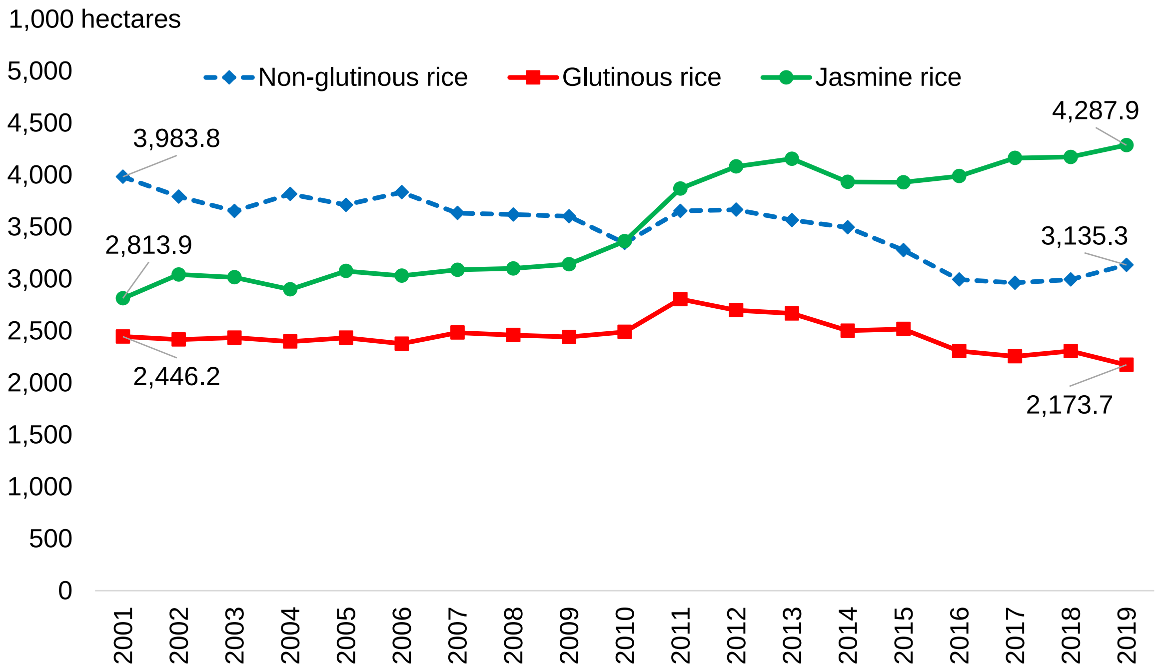

Figure 1.6 Rice growing areas by type of rice varieties

Source: Data from Office of Agricultural Economics (2019b)

In terms of production, Figure 1.6 shows that Jasmine rice production increased by around 73.9%, from 5.1 million tons in 2001 to 8.9 million tons in 2019. In terms of yield, Figure 1.8 shows that, in 2019, the Jasmine rice yield was approximately 2.4 ton per hectare, which is substantially lower than the Non-glutinous rice yield (3.6 ton per hectare).

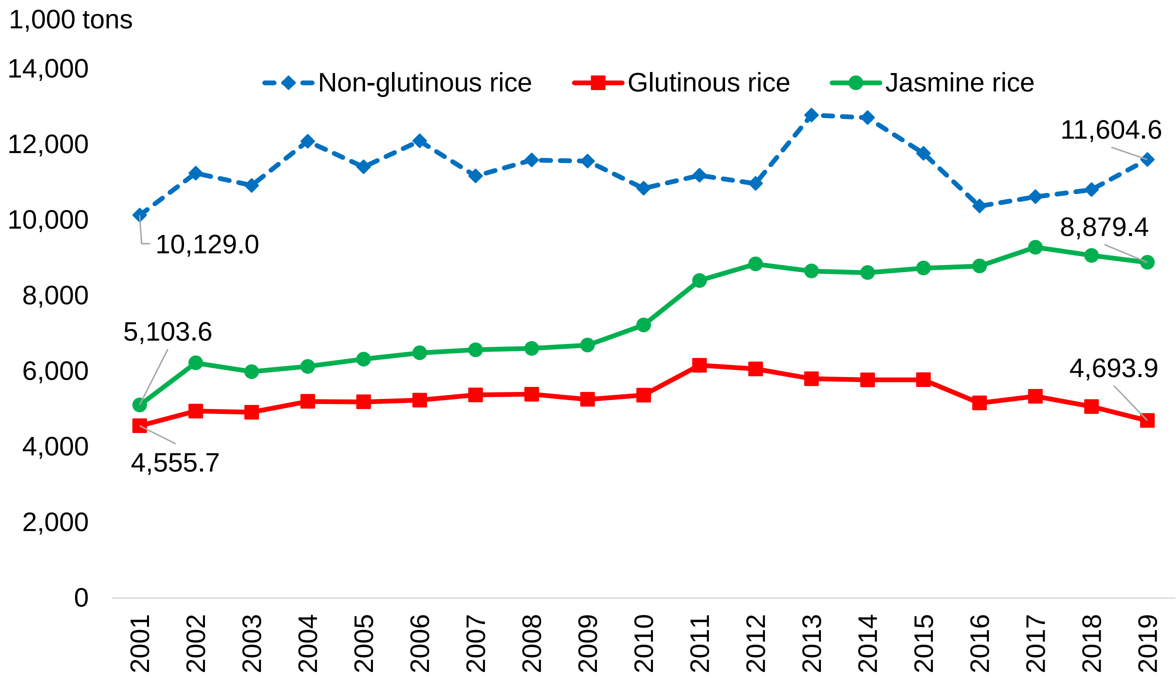

Figure 1.7 Rice production by type of rice varieties

Source: Data from Office of Agricultural Economics (2019b)

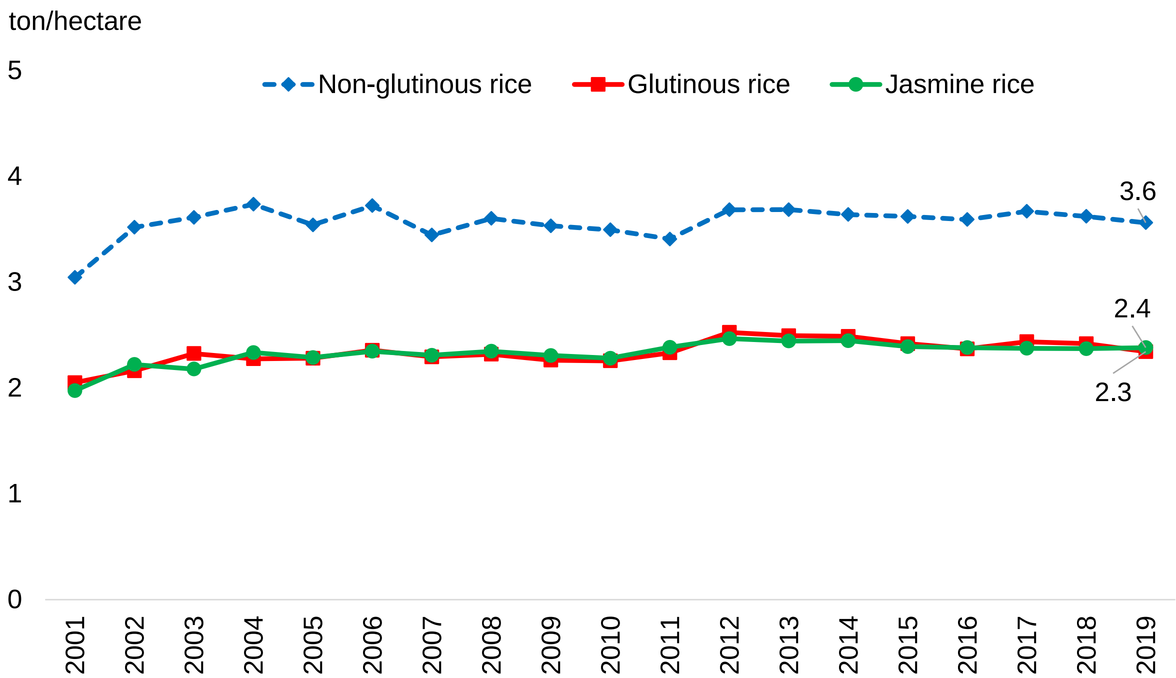

Figure 1.8 Rice yield by type of rice varieties

Source: Data from Office of Agricultural Economics (2019b)

In the past two decades, Jasmine rice markets have undergone two key structural changes that raise a concern about the functioning of markets. First, there has been significant disintermediation in the Jasmine rice value chains. Disintermediation refers to when one or more segments of the value chains are cut out (Reardon et al., 2014). In our case, millers are increasingly getting around traditional middlemen such as village traders and are buying directly from farmers. Figure 1.9 shows that the role of traders substantially declines in the Jasmine rice value chains. The percentage of paddy volume sold to traders by farmers significantly reduce from 40.1% in 1999 to 9.5% in 2018. In contrast, the percentage of paddy volume sold to millers by farmers substantially increase from 35.5% in 1999 to 76.2% in 2018.

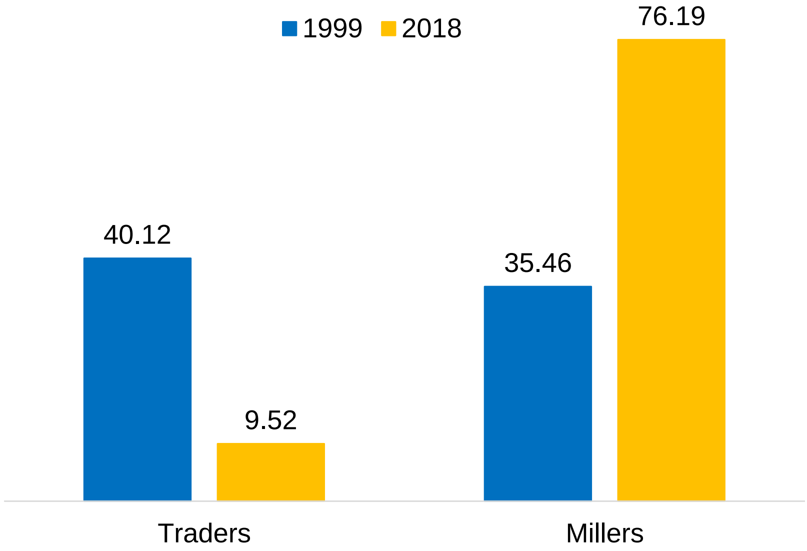

Figure 1.9 Farmer marketing channels in 1999 and 2018

Source: Data from Office of Agricultural Economics (2019a, 1999)

As traders play a significant role in trade across regions, the reduction in their role may decrease spatial market integration and spatial competition. Namely, when there is a price difference between markets, traders motivated by arbitrage opportunities will play a key role in facilitating trade between markets. These countless transactions across markets by traders are necessary to achieve spatial market integration and perfect cross-market competition. Hence, without traders, spatial market competition may substantially decrease.

Second, rice millers have become fewer and bigger. This structural change is in line with the on-going trend in consolidation and concentration in the mill segment in Asia's rice value chains. This trend is partly driven by the need to feed a massive and growing population in urban areas (Reardon et al., 2014). In Thailand, the number of commercial rice mills, which have milling capacity greater than 5 tons per day, decreased by 10.2% from 1,729 in 2006 to 1,553 in 2015, whereas the milling capacity substantially increased by 70.5% from 177,399 tons per day in 2006 to 302,458 tons per day in 2015. As rice production in Thailand is approximately 29.5 million tons per year, the rice milling industry is now experiencing overcapacity (Titapiwatanakun, 2012). This overcapacity situation creates a barrier to entry into the rice milling industry because the financial sector is unlikely to finance the new investment in rice mills. This market structure raises the concern that millers may exercise market power to depress the price paid to farmers. Specifically, the rice millers have a share incentive to keep the high spread between output price (milled rice) and input price (paddy). As a result, they may have a low incentive to compete. On the contrary, they may have a strong incentive to exercise market power to drive down the farm gate price. They can do so in at least three ways. First, they can coordinate to offer the same low price. Second, they can engage in price discrimination among sellers. Lastly, they can use non-price exploitations such as weight and moisture to lower the price paid. Overall, the structural changes in the Jasmine rice markets may allow rice millers to enjoy spatial oligopsony power over farmers.

1.2.3 Policy interventions in Jasmine rice markets

Throughout my study period, Jasmine rice markets experienced the frequent changes of government policies that are caused by political instability, such as military coups. Figure 1.10 shows the major policy interventions in Jasmine rice markets and its relationship with each chapter in this dissertation.

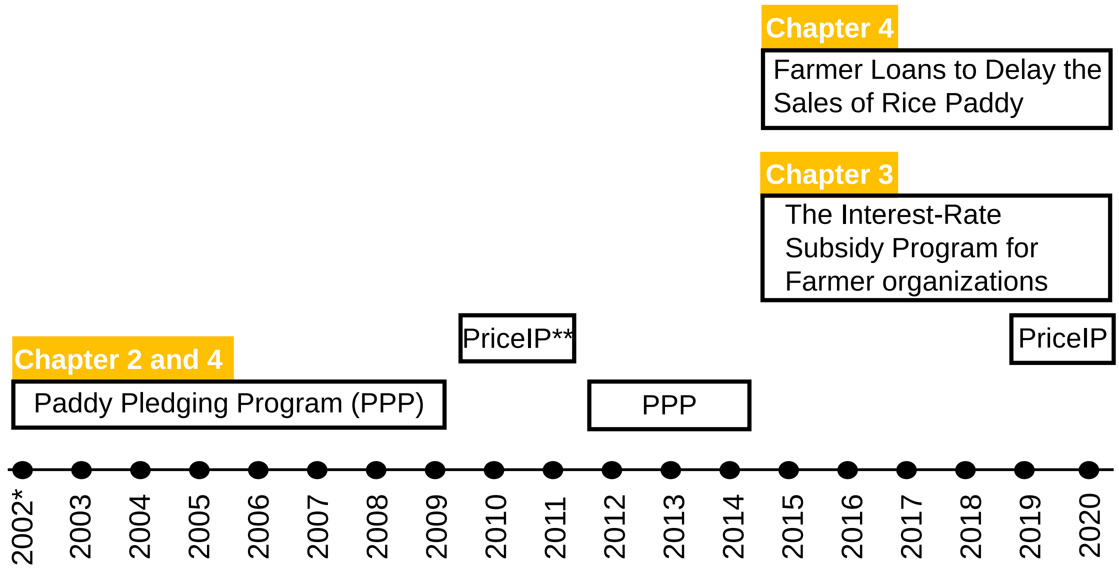

Figure 1.10 Timeline of policy interventions in the Thai Jasmine rice markets and its relationship to each chapter in this dissertation.

Note: 2002* = Crop marketing year (MY) 2001/2002, I define MY2001/02 as November 1, 2001 to October 31, 2002, **Price Insurance Program

I) Paddy Pledging Program (PPP)

Paddy pledging program (PPP) was a key intervention that the Thai government use to support rice prices and increase farmers' income between 2002 and 2009 and between 2012 and 2014. Under this program, the government offers farmers loans during the harvesting season (November to February). The government allows farmers to borrow in two ways. First, farmers can borrow directly from the Bank for Agriculture and Agricultural Cooperatives by keeping paddy in storage facilities on their farms as collateral (on-farm paddy pledging). Second, farmers can borrow by bringing their paddy to registered rice mills (warehouse deposit slip pledging). The rice millers will then issue warehouse receipts for farmers to get loans from the Bank Agriculture and Agricultural Cooperatives. The loan values equal the support price (or the pledging price) times paddy quantity put under the loans. The loans are made for four months. If the paddy market price increases sufficiently during the loan period, the farmer may pay off the loan plus interest and regain control of his/her rice. In contrast, if the paddy market price is not sufficiently above the support price when the loan comes due, the farmer can then freely default. The government agrees to accept paddy as full reimbursement. As the government set the support price approximately 20.1% higher than the market price, most farmers defaulted. Therefore, we can consider the paddy pledging program as a price support policy.

II) The Interest-Rate Subsidy Program for Farmer Organizations

The interest-rate subsidy program for farmer organizations is designed to enhance farmer organizations' role in the Jasmine rice value chains. Many problems such as undercapitalization, lack of member commitment, and poor management have limited the role of farmer organizations in the Jasmine rice value chains. Since 2015, the Thai government has implemented interest-rate subsidy program with yearly loan values equal $410 million to solve the undercapitalization problem. Under this program, farmer organizations can borrow money from the Bank for Agriculture and Agricultural Cooperatives to buy paddy from farmers (both members and non-members). Famer organizations pay only 1 percent interest rate; the government will subsidize the rest (3%). This program allows farmer organizations to compete with private intermediaries to buy rice from farmers.

III) Farmer Loans to Delay the Sales of Rice Paddy or On-farm Paddy Pledging

The farmer loan program is designed to help individual farmers who need money during the harvesting season but would like to delay their paddy sales. This program is a modified version of the paddy pledging program and has been implemented since 2015. Unlike the paddy pledging program, there is only one way for farmers to get a loan. That is, farmers can borrow only by keeping their paddy on-farm as collateral. Moreover, this program's pledging price is much closer to the market price than the paddy pledging program. Further, the government provides a storage cost subsidy to farmers, whereas no storage cost subsidy is offered under the paddy pledging program.

1.3 Objectives of the study

This dissertation attempts to deepen our understanding about the effect of policy interventions on the functioning of agricultural markets in advanced developing countries. Three agricultural policy interventions in the Thai Jasmine rice markets are used as a case study. The specific objectives of the study are:

- To evaluate the welfare effect of paddy pledging program or price support policy using imperfect competition model
- To evaluate the spillover effect of direct competition (caused by the interest-rate subsidy program) between farmer organizations and private intermediaries
- To evaluate the effect of on-farm storage interventions or farmer loan program on local farm gate prices

1.4 Significance of the study

Raising smallholder farmers' income is at the core of agricultural policy in many developing countries. This is because enhancing farmers' income is vital for achieving food security and promoting sustainable agriculture. Many smallholder farmers persistently struggle with poverty, in part due to unfavorable market outcomes. This dissertation empirically evaluates the effect of three policy interventions on the market outcomes, such as the price received by farmers. Although my analysis is based on the Thai experiences, results can benefit other developing countries' policymaking. Specifically, this dissertation provides crucial evidence for agricultural policy debates regarding i) the welfare effect of price support policy in the presence of market power, ii) the role of farmer organizations in agricultural development and agricultural markets, and iii) the welfare implications of on-farm storage interventions when delivered on a massive scale.

This dissertation also fills knowledge gaps in agricultural economic literature in three important areas. First, to the best of my knowledge, the study in chapter 2 is the first study to examine the welfare effect of price support policy under imperfect competition in developing countries. Second, chapter 3 provides the first empirical evidence of the existence and magnitude of the spillover effect of marketing cooperatives. Lastly, to the best of my knowledge, chapter 4 is the first study to detect market-level effects of on-farm storage interventions by taking advantage of panel data.

1.5 Outline of the dissertation

Chapter 1 of the dissertation gives a general introduction, chapters 2 to 4 are a collection of three journal articles, and chapter 5 presents conclusions and policy implications. Specifically, chapter 2 develops an imperfect competition model to evaluate the welfare effect of price support policy empirically. Chapter 3 empirically examines the causal relationship between the presence of marketing cooperatives in input markets and the price received by farmers. Chapter 4 assesses the market-level effect of on-farm storage intervention when delivered at scale. The last chapter summarizes the results and policy implications and discusses avenues for further research.

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Chapter 2 Does oligopsony power matter in price support policy design? Empirical evidence from the Thai Jasmine rice market

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Abstract

In the oligopsony market, farmers may receive low prices and policy analysis assuming perfect competition can yield serious bias results. In this article, we estimate oligopsony power between processors and farmers and evaluate the welfare impact of the paddy pledging program (PPP), a generous price support program in the Thai Jasmine rice market, with an imperfect competition model. We develop a model that consists of rice supply equation and derived demand equation. We then simultaneously estimate these equations using system estimation methods to recover oligopsony power parameters. Lastly, we use these parameters to assess the welfare impact of the price support program. Using annual panel data running from crop marketing year 2001/02 to 2015/16 and exploiting the institutional feature of the PPP, we find strong evidence of some oligopsony power, a moderate level of oligopsony price distortion, and a negative relationship between price support and oligopsony power. We also find that the PPP is inefficient but effective in income redistribution. Moreover, the program benefits both farmers and consumers. With better policymaking decisions, the PPP can be efficient by setting a suitable support price. Therefore, our results show that in the case of the Thai Jasmine rice market, the generally accepted "wisdom" about agricultural price support policy does not necessarily hold, and price support can be designed to improve the efficiency of the market.

Keywords: Oligopsony power, price support policy, welfare analysis, rice, Thailand
JEL classification: L13, Q18

2.1 Introduction

The agricultural price support policy is a key policy instrument used by governments in developing countries to increase farmers' income. The perceived wisdom regarding this policy is that it benefits farmers, hurts consumers, and imposes a deadweight loss on society (Pindyck and Rubinfeld, 2009). These conclusions have been used to promote the complete elimination of the price support program (OECD, 2017). However, despite the growing evidence of imperfect competition in agricultural markets, most assessments of price support policy maintain the assumption of perfect competition (Russo et al., 2011). Little effort has gone into investigating the welfare effect of price support policy using an imperfect competition model, even though much of literature indicates that the evaluation of agricultural policies is sensitive to the form of competition specified in the model (e.g. Huang et al., 2006; Russo et al., 2011; Sexton and Lavoie, 2001). Moreover, despite a general concern regarding the existence of oligopsony power[4] in grain markets in developing countries (Banerji and Meenakshi, 2004), the importance of oligopsony power in grain policy evaluation and price support design have been ignored.

Given the above, in this paper we address two important questions: First, how much oligopsony power do processors or intermediaries in the Thai Jasmine rice market have and exercise over farmers? Second, what are the market and welfare effects of price support policy in the presence of oligopsony? Few studies have investigated oligopsony power in rice markets in developing countries. Hayami et al. (1999) and Dawe et al. (2008) find no evidence of collusion among traders in the Philippines's rice market. Moser et al. (2009) also find no evidence of imperfect competition in Madagascar's rice markets. However, none of these studies directly estimates the degree of oligopsony power.

Our paper contributes to the empirical literature on competition in rice markets in a developing country by directly estimating oligopsony power. We develop a rice market model based on the New Empirical Industrial Organization (NEIO) framework. This framework has

[4] In the presence of oligopsony power, farmers may receive a low farm gate price, and the wealth is transferred from farmers to intermediaries. This transferred wealth, in turn, limits farmers' profitability and distort their incentive to invest (Sexton, 2013).

a firm foundation in economic theory (Kaiser and Suzuki, 2006) and has been widely used to directly estimate oligopsony power in developed countries' food industry (e.g. Anders, 2008; Chung et al., 2018; Evans and H. Ballen, 2016; Grau and Hockmann, 2017; Morrison Paul, 2001; Muth and Wohlgenant, 1999). A shortcoming of the NEIO approach is that yearly data cannot be used to estimate oligopsony power in rice markets[5] because rice supply at any point in time is fixed by planting decisions made the previous year (Sexton and Lavoie, 2001). As a result, rice markets in developing countries have not been subjected to standard NEIO imperfect competition analysis. In this study, our econometric model exploits the institutional feature of the price support program to allow supply to vary so that the NEIO approach[6] can be used. Thus, our paper sheds light on the issue of competition in rice markets in a developing country by applying modern industrial organization concepts.

Our research also contributes to the literature by developing an imperfect competition model to evaluate price support policy. Although a number of studies (Hamilton and Sunding, 1998; Sexton et al., 2007; Suzuki et al., 1993; Suzuki and Kaiser, 1997) have indicated that a failure to incorporate imperfect competition parameters in agricultural policy evaluation can lead to serious bias results, prior studies[7] of Thai rice price support policy, locally known as the paddy pledging program (PPP) (e.g. Duangbootsee and Myers, 2015; Permani and Vanzetti, 2016; Poapongsakorn, 2010), assume perfect competition assumption. In this paper, we develop the imperfect competition model based on the theoretical work of Russo et al. (2011) to evaluate price support policy in the Thai Jasmine rice market where the intermediaries may exercise oligopsony power. As price support can reduce intermediaries' oligopsony power, assuming imperfect competition allows us to estimate its redistribution effect, i.e., welfare

[5] Unless we have a precise estimate of farmers' price expectations.

[6] Although the NEIO approach has been subjected to intense criticism since Corts's paper (1999) , we consider it a valid option for the case at hand. We discuss the limitations of the method in section 4.1.

[7] These studies reveal several drawbacks of the PPP that are in line with the generally accepted "wisdom" about agricultural price support policy. Therefore, earlier studies have recommended that Thailand eliminate the PPP. The Thai government did so in mid-2014, despite concerns about the functioning of the Jasmine rice market.

transfer to farmers and consumers at the expense of intermediaries. Economists have paid relatively little attention to this effect, even though they widely agree that the goal of price supports is not to promote efficiency but to redistribute income to farmers (Acemoglu, 2001). Using an imperfect competition model also allows us to show how policymakers can design price supports to improve social welfare. This information will benefit policymakers in many developing countries where price support programs remain in place to support farmers' income.

The remainder of the paper is structured as follows. The next section describes the Jasmine rice market structure and the PPP. The section that follows explains our theoretical framework. We then illustrate the estimation strategy and data used in our analysis, followed by estimation results. The last section concludes.

2.2 Background

2.2.1 A brief overview of the Jasmine rice market

The processors or intermediaries in the Jasmine rice market may have some oligopsony power over farmers for three important reasons. First, currently, 1.9 million small farm households produce Jasmine rice, which only approximately 457 rice millers[8] purchase (Rice Department., 2016). Second, there may be barriers to entering the rice milling industry due to overcapacity (Isvilanonda, 2010) and the high cost of doing business. Third, the high transportation cost of paddy has limited farmers' selling options to only nearby buyers. Overall, these conditions jointly suggest that intermediaries may enjoy spatial oligopsony power over farmers.

2.2.2 Government price support policy in the Jasmine rice market

Price support policy in the Thai Jasmine rice market provides an interesting case study. In the past, the Thai government had used price support policy, locally known as the paddy pledging program (PPP),[9] to increase rice price and farmers' income. Under the program, the government offers loans to farmers at harvest time (November to February) with their paddy

[8] In 2008, an estimated 80-90% of all paddy rice was sold to rice millers (Isvilanonda, 2010).

[9] This program covered not only Jasmine paddy, but also non-glutinous paddy and glutinous paddy. Jasmine paddy accounted for only 20.2% of total pledged paddy during our sample period.

pledge as collateral. If farmers choose to default, the government agrees to accept paddy as full reimbursement. In this setting, the government serves as an alternative buyer for paddy, setting an effective (but not legislated) price support. Since the government does not legislate a price floor, some farmers experience market prices that are below support price. It is this population of noncompliers[10] who participate in the local market, wherein we observe market price. During our sample period, the marketing year (MY) 2001/02[11] to 2015/16, on average, the government set the support price approximately 20.1% higher than the market price. As a result, the government purchased a significant amount of paddy (see Figure 2.1).

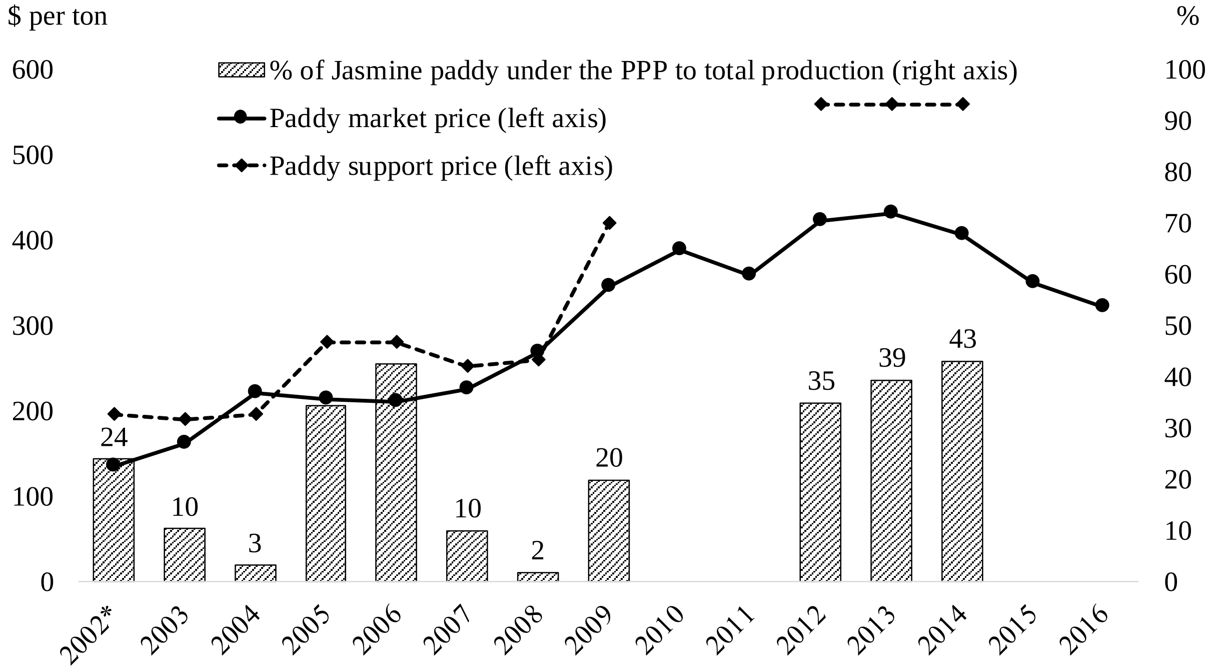

Figure 2.1 The Jasmine paddy market price (nominal price), the Jasmine paddy support price (nominal price), and % of paddy under the paddy pledging program to total production
Note: 2002* = MY2001/200, Source: based on data from the Department of Internal Trade, Isvilanonda (2010), Poapongsakorn (2010), and the Office of Agricultural Economics

[10] Some farmers might remain non-compliers because of the long distance from farmers' farm to the government procurement points or because of operational constraints such as delay in payments. We discuss the implication of having an imperfect policy coverage in section 3.2.

[11] Note: we define MY2001/02 as November 1, 2001 to October 31, 2002.

2.3 A theory framework

2.3.1 A theoretical model of the oligopsony rice market

We adopt Muth and Wohlgenant (1999)'s model of the oligopsony market. Suppose that the rice millers or the intermediaries have an oligopsony power. They buy paddy (input) from farmers and sell milled rice (output) to consumers. Assume that the inverse rice supply equation is

$$P^f = G(Q, Z) \tag{2.1}$$

where P^f is the farm gate price, Q is the rice supply, and Z is a vector of supply sifters. Rice milling is assumed to utilize a fixed proportion and constant return technology. In this case, we can denote both paddy and milled rice by the same variable, Q.

Let π_i be the rice miller's profit function for rice miller i.

$$\pi_i = P^w \cdot q - P^f q - C(q, V) - T(q, L) \tag{2.2}$$

for $i = 1, \ldots, n$ where $P^f = G(Q, Z)$ as in Equation (2.1), $P^w$is wholesale price, $C(q, V)$ is constant processing costs per unit of paddy rice processed, $T(q, L)$ is transportation cost, V and L are a cost shifter. Assume that the output market is competitive. The firm maximizes its profit by setting the derivative of profit with respect to input equal to zero. If the input market is perfectly competitive, we have input price equal to the value of the marginal product (VMP).

$$P^f = P^w - \partial C(q, V)/\partial q - \partial T(q, L)/\partial q \tag{2.3}$$

However, if the firm is monopsonist, the first order condition becomes

$$P^f + \theta(\partial G(Q, Z)/\partial Q)Q = P^w - \partial C(q, V)/\partial q - \partial T(q, L)/\partial q \tag{2.4}$$

where θ indexes the degree of oligopsony power. If $\theta = 0$, the first order condition reduces to Equation (2.3). Hence, the market is perfectly competitive. If $\theta = 1$, the marginal factor cost equals the marginal factor cost of the monopsonist. Therefore, firms are perfectly collusive or monopsonist. The intermediate values of θ indicate various magnitudes of oligopsony power. Solving for P^f gives the derived demand equation.

$$P^f = -\theta(\partial G(Q,Z)/\partial Q)Q + P^w - \partial C(q,V)/\partial q - \partial T(q,L)/\partial q \qquad (2.5)$$

Equations (2.1) and (2.5) are the standard expression of the oligopsony pricing equation estimated in the NEIO framework. Equation (2.4) can be written in elasticity form as

$$P^f(1 + \theta/\varepsilon) = P^w - \partial C(q,V)/\partial q - \partial T(q,L)/\partial q \qquad (2.6)$$

where $\varepsilon = \frac{\partial Q}{\partial P^f}\frac{P^f}{Q}$ is the price elasticity of paddy supply. Since the value of the marginal product and the farm gate price would be equal if the market were competitive, the difference between VMP and P^f is an index of the relative oligopsony price distortion. Rearranging Equation (2.6), we obtain $M = \theta/\varepsilon$, where M measures the oligopsony power distortion of the rice millers.

2.3.2 An analytical framework for the welfare impact of a price support policy

We develop an analytical framework based on the theoretical work of Russo et al. (2011). Unlike Russo et al. (2011), however, we assume intermediaries to exert market power only in the procurement market. Moreover, we relax the assumptions that all farmers participate in the program and the government stock has no value to reflect the reality of the price support policy in many developing countries. In addition, we also include income redistribution effect in the model.[12] Figure 2.2 presents the cases for market equilibrium under a price support policy when the government sets the support price higher than the competitive price ($P_S > P_C$). We relax the perfect policy coverage assumption by introducing a policy coverage parameter[13] (γ) which has a value

[12] We maintain a closed economy assumption by utilizing a total Jasmine rice market demand curve and considering the Jasmine rice market as one market.

[13] γ is endogenous because the market price is affected by *MFC*, *MFC* is affected by γ, and γ is affected by P_S and other factors. The referee points out that this may cause P_S to be endogenous. However, we

of between 0 and 1. By doing so, the new marginal factor cost (MFC_2) equals $(1-\gamma)MFC_1 + \gamma P_S$. If $\gamma = 1$, the MFC_2 is perfectly elastic at P_S for $Q \leq Q_S$, as in the perfect policy coverage setting in Russo et al. (2011). In contrast, in the complete absence of policy coverage so that $\gamma = 0$, the MFC_2 is independent of the support price and coincides instead with the unregulated MFC_1. Smaller values of γ represent greater departures from perfect policy coverage.[14]

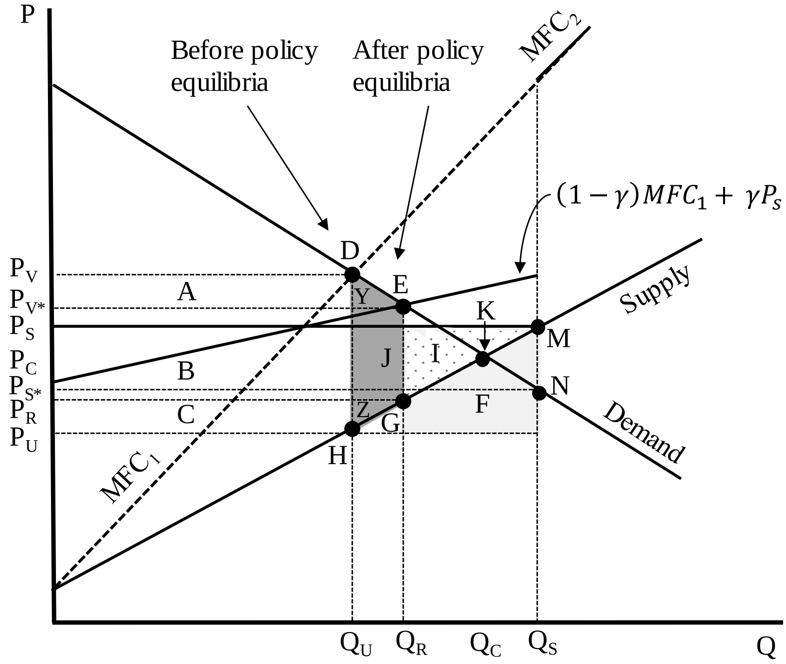

Figure 2.2 The efficiency and redistribution effects of the price support policy.

Note: The U and R subscripts denote whether the market is unregulated or regulated (under the price support program). The C and S subscripts indicate competitive equilibrium and the government support price, respectively.

Considering the case of imperfect policy coverage, the floor price reduces a welfare loss from triangle DKH to triangle EKG. Hence, the price floor increases welfare by trapezoid Y+J+Z.

believe that, as also noted by the referee, we can take P_S as exogenous from the point of view of the model because the model does not explain the variability of P_S, i.e., its variability is explained by the political regime.

[14] Because of imperfect policy coverage, intermediaries can pay below the floor price and only farmers who participate in the PPP will receive the floor price.

Moreover, as the government buys a quantity Q_S, the producer's surplus increases by the speckled triangle I. Thus, the total change in welfare or efficiency effect is (Y+J+Z+I) – Net cost to government which equals purchasing cost ($P_S(Q_S - Q_R)$) + processing cost + sack cost + transportation cost + storage cost + operating cost + interest cost + quality depreciation cost – revenue from selling milled rice. Next, we consider the income redistribution effect. The price floor reduces oligopsony profits from square $P_V DHP_U$ to square $P_{V*}EGP_R$. Thus, the price floor transfers the welfare from intermediaries to farmers and consumers equal to area A and C, respectively. In addition, the government transfers income from taxpayers to farmers equal to area F (the light-shaded area). Hence, the total income redistribution effect is A+C+F.

2.4 Estimation strategy

2.4.1 Estimate the oligopsony power parameters

To identify and estimate θ in the optimal equation, we employ the general identification method (GIM) used in the NEIO literature. The identification concept of GIM is that the current price must affect the current supply, and we must model supply in such a way that its slope can vary over time (Jeffrey et al., 2007). We use the interaction between farm gate price and lagged fertilizer price for that purpose.[15] As it is usually difficult to obtain firm-specific data in developing countries, our econometric specification is based on industry data.

The empirical analog to Equation (2.1), the Jasmine rice supply equation, is given as

$$Q_{it} = \alpha_0 + \alpha_1 P_{it}^f + \alpha_2 ferp_{t-1} + \alpha_3 P_{it}^f * ferp_{t-1} + \alpha Z_{it} + \alpha Z_{i(t-1)} + a_i + u_{1it} \quad (2.7)$$

where *i* denotes province, and *t* denotes the time period. Q_{it} is the quantity of Jasmine paddy supply and P_{it}^f is the average Jasmine farm gate price. Because there is one marketing year lag between planting and the resulting production, lagged variables such as climate conditions

[15] Suppose fertilizer price increases; if the supply function does not have an interaction term, this shock causes a parallel shift in the supply curve. In contrast, if the supply function has an interaction term, the supply curve shifts and rotates.

and input prices are used in explaining Jasmine rice supply. $Ferp_{t-1}$ is lagged national fertilizer price,[16] $P_{it}^{f} * ferp_{t-1}$ is an interaction term, Z_{it} and $Z_{i(t-1)}$ are the vectors of other supply shifters, which include a dummy variable relating to government policy, time trend, lagged rain, the quadratic term of lagged rain, lagged farm gate price, lagged minimum wage, and the lagged price of competing crops; a_i is province fixed effects and u_{1it} is the error term. To complete the model, we specify a reduced-form of the VMP as follows:

$$VMP = \beta_0 + \beta_1 P_t^w + \beta C_t + \beta C_{it} + u_{2it} \tag{2.8}$$

where P_t^w is the wholesale Jasmine rice price index,[17] C_t and C_{it} are cost shifter vectors, which include minimum wage, electricity price, diesel price, and time trend; u_{2it} is error term. Substituting VMP and $\partial G(Q,Z)/\partial Q_{it}$ from supply Equation (2.7) into Equation (2.5) yields the final empirical specification of derived demand relation:

$$P_{it}^{f} = \beta_0 - \theta Q_{it}^{*} + \beta_1 P_t^w + \beta C_t + \beta C_{it} + \mu \tag{2.9}$$

where $\mu = u_{2it} - u_{1it}$, and $Q_{it}^{*} = \frac{Q_{it}}{\alpha_1 + \alpha_3 ferp_{t-1}}$. Following Morrison Paul (2001), we specify the oligopsony power parameter as a linear function of specific variables to allow equilibrium conjectures to vary with market conditions. Since the government support price may have an

[16] The level of fertilizer price may be different among provinces. However, as we use the price change in our estimation, using the national fertilizer price will not lead to bias estimators because the fertilizer price in the first difference is expected to be homogenous among the provinces due to the government price control law and the oligopolistic structure of the fertilizer market in Thailand (Chitibut et al., 2014).

[17] The wholesale Jasmine rice price index is used to represent the price that the rice miller receives per ton of paddy bought. This price index is calculated based on the Jasmine rice milling conversion rate, wholesale Jasmine rice price and the price of by-products. We use the wholesale Jasmine rice prices in Bangkok as a proxy for the local wholesale rice prices because these prices have been used as a reference price by rice millers nationwide. Moreover, although the level of wholesale prices varies among provinces, we expect an infinitesimal difference in the change in wholesale price among provinces.

impact on oligopsony power, we specify oligopsony power as a linear function of the difference between market price during the harvesting period (November to January) and government support price ($pdifgovmar_{it}$). In addition, because the structure of the industry has changed over time, we specify oligopsony power as a linear function of time trends ($ttrend$). We have $\theta = \theta_I + \theta_G pdifgovmar_{it} + \theta_T ttrend$ to substitute into Equation (2.9). Equations (2.7) and (2.9) comprise the system of equations that allow us to estimate oligopsony power in the rice market. A general criticism of NEIO studies is that the NEIO approach is biased if the underlying game is dynamic and nonlinear (Russo, 2012). In an output market counterpart to our model, Russo (2012) establishes that the NEIO approach becomes unbiased if we control for nonlinear supply relation. Applying the same logic to the input market model, our oligopsony power specification has addressed the nonlinear demand relation.

Our estimation has four econometric problems. First, we have a simultaneity problem, as farm gate price is jointly determined with rice supply. To solve this problem, we apply the three-stage least squares method for panel data. Second, we may omit some variables such as the province's location and farm practices. We solve this problem by using the first difference to eliminate omitted variables[18] (Wooldridge, 2010). The first difference also eliminates the unit root problem in our time series data. Third, we may have spatial correlation across neighboring provinces. We believe such a correlation is largely captured through the fixed effect a_i, and thus its elimination via the first difference effectively solves the problem (Wooldridge, 2006). Lastly, we have a simultaneity problem from the endogenously determined wholesale Jasmine rice price index in the derived demand equation. To solve this problem, we use the Thai population variable and exchange rate variable as instrument variables. These two variables have no direct effect on farm gate price but correlate with the wholesale Jasmine rice price index.[19]

[18] Since location and farm practices are constant over one year, we can difference away these variables.

[19] Wholesale rice price index and Thai population (exchange rate) have a statistically significant positive correlation (the *p*-value = 0.024 (0.000)). The F-statistic from the first stage regression of the derived demand equation equals 194.5; this value shows that the instrument has sufficient power.

2.4.2 Simulate the Jasmine rice market under the PPP

We observe P_S, P_R, Q_R, and Q_S in the Jasmine rice market. Therefore, we need to estimate P_C, Q_C, P_U, Q_U, P_V, P_{V*}, and P_{S*} (see Figure 2.2). To do so, we substitute the estimated values from 2.4.1 and observed values in the Jasmine rice market into the following equations: 1) $P_{V*} = P_R(1 + \theta_R/\varepsilon)$ where θ_R is oligopsony power under a regulated market or price support program; 2) $P_V = P_U(1 + \theta_U/\varepsilon)$ and $P_U = P_V/(1 + \theta_U/\varepsilon)$ where θ_U is oligopsony power under a unregulated market or no price support program; 3) $Q_U = Q_R + (\widehat{\Delta Q_U} - \Delta Q_R)$ where $\widehat{\Delta Q_U}$ is the estimated change in supply under the unregulated market and ΔQ_R is actual supply change; 4) $P_{S*} = P_{V*} + (\widehat{\Delta P_{S*}} - \widehat{\Delta P_{V*}})$ where $\widehat{\Delta P_{S*}}$ is the estimated change in price at P_{S*} and $\widehat{\Delta P_{V*}}$ is the estimated change in price at P_{V*}; and 5) To obtain competitive equilibrium (P_C, Q_C), we first solve for the linear approximation of derived demand and supply based on points D, E, N and H,G,M (see Figure 2.2) and then solve the demand equation and supply equation. Further detailed calculation procedures are discussed in Appendix A[20].

[20] Appendix can be found online in the supporting information section at https://doi.org/10.1111/agec.12560.

2.5 Data

We construct a data set from 9 data sources. The data are annual,[21] with 15 provincial level observations within two regions (only 1 province is at different regions), running from marketing year 2001/02 to 2015/16, providing 225 observations before taking first differences. The Jasmine paddy rice supply is constructed based on data from the Agricultural Data Operation Center of The Office of Agricultural Economics, The Ministry of Agriculture and Cooperatives (MAC). The farm gate price data are from the Office of Agricultural Economics. The fertilizer price variable is constructed from Thailand's Trading Database, The Ministry of Commerce (MOC). Rainfall data are from Climatic Data Service Center of the Thai Meteorological Department, The Ministry of Digital Economy and Society. The wholesale Jasmine rice price index variable and price support dummy variable are calculated based on data from The Department of Internal Trade, The Ministry of Commerce. Minimum wage data are from The Ministry of Labor (MOL). Thai population data are from The Department of Provincial Administration, The Ministry of Interior (MOI). The exchange rate, fuel oil price, and diesel price are from The Bank of Thailand (BOT). All price and income variables were deflated using the consumer price index with base year 2015 from The Bureau of Trade and Economic Indices. Details on variables are provided in Appendix B. Table 2.1 presents the descriptive statistic for the full sample and the main growing areas[22] sample.

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[21] Ideally, one would like to have monthly data. Unfortunately, such data are unavailable, specifically for the Jasmine paddy rice supplied variable.

[22] The top 6 largest Jasmine rice-producing provinces account for 61% of total Jasmine rice production. We perform an analysis in this subsample to learn about oligopsony power in high-surplus areas.

Table 2.1 Summary statistics

Variable	Full sample		Main growing area		Unit	Source
	Mean	Std. dev.	Mean	Std. dev.		
Δjasmine paddy production	15.1	133.1	30.9	207.0	1,000 tons	Constructed
Δfarm gate price	219.8	1,792.7	197.2	1,944.6	Baht per ton	MAC
Δfertilizer price	9.0	486.8	9.0	488.6	Baht per 50 kilograms	MOC
Δfarm gate price*fertilizer price	204,003	8,194,318	190,437	8,705,802	-	Constructed
Δprice support dummy	-0.1	0.7	-0.1	0.6	-	Constructed
Δlagged rain in quarter 3	-0.0	35.7	-0.8	46.9	Millimeter per quarter	Constructed
Δ(lagged rain in quarter 3)^2	-55.8	11,052.6	-217.6	15,845.1	Millimeter per quarter	Constructed
Δlagged rain in October	0.5	57.7	-0.7	81.9	Millimeter per month	Constructed
Δ(lagged rain in October)^2	13.7	15,305.5	-212.3	22,293.8	Millimeter per month	Constructed
Δlagged sugarcane farm gate price	6.3	100.5	6.3	100.9	Baht per ton	MAC
Δlagged cassava farm gate price	75.5	444.4	75.5	446.0	Baht per ton	MAC
Δlagged minimum wage	8.0	22.7	7.9	22.8	Baht per day	MOL
Δlagged farm gate price in quarter 2	350.4	2,143.3	352.4	2,315.6	Baht per ton	MAC
Δdiesel price	0.4	4.4	0.4	4.4	Baht per liter	BOT
Δminimum wage	8.1	22.7	8.0	22.8	Baht per day	MOL
Δfuel oil price	0.4	3.5	0.4	3.5	Baht per liter	BOT
Δwholesale price index	342.1	1,825.4	342.1	1,831.9	Baht per ton	Constructed
ΔThai population	223,691	416,432	223,691	416,432	People	MOI
Δexchange rate	-0.6	1.7	-0.6	1.7	Baht per dollar	BOT
pdifgovmar	1,779.2	2,199.5	1,647.8	2,139.0	Baht per ton	Constructed
Observations	225		90			

2.6 Estimation results and policy implication

2.6.1 Oligopsony power parameters

We begin our analysis by testing the properties of the panel data. The results of the Harris-Tzavalis unit-root test show that most price variables in levels have unit roots (see Table C1 in Appendix C). In contrast, all variables in first differences are stationary. The Westerlund test statistic and one out of three Pedroni's test statistics indicate no cointegration (see Table C2 in Appendix C). As the cointegration test is inconclusive, in the end we chose the analysis that does not cover a long-run relationship and is more consistent with the NEIO. Namely, we simultaneously estimate the supply and derived demand equation using system estimation methods instead of the error-correction model.

Table 2.2 shows the estimation results. The Wooldridge test for autocorrelation shows that Δu_{1it} and $\Delta\mu$ are uncorrelated over time for both supply equation and derive demand equation (except in column 8). Both equations also have no heteroscedasticity problem, as the Breusch-Pagan test for heteroscedasticity results in a high p-value. Table 2.2 also shows that the farm gate price variable, the fertilizer price variable, and their interaction are statistically significant at the 1% significance level. Therefore, an interaction term between rice price and fertilizer price rotates the supply curve, which in turn enables us to identify the oligopsony power parameters.

Regardless of model specifications, estimates of the oligopsony power component (θ) are mostly significantly different from zero at the 1% significance level. In column 1, as expected, there is a negative relationship between government support price and oligopsony power. The coefficient on θ_G is negative and highly statistically significant ($p < .001$). This means that the positive price spread between support price and market price is predicted to decrease oligopsony power. This makes intuitive sense because when the government sets the support price higher than the market price, farmers are more likely to participate in the program, which in turn will increase the effectiveness of price support in eliminating oligopsony power.

Table 2.2 Summary I3SLS and N3SLS estimations of the supply equation and perceived demand equation

Variables	Full sample				Main growing area			
	I3SLS	N3SLS	I3SLS	I3SLS	I3SLS	N3SLS	I3SLS	I3SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Perceived demand equation, dependent variable: farm gate price (ΔP^f)								
Δdiesel price	-70.5**	-70.0**	-112.0***	-82.1***	-66.8	-68.2	-102.5***	-123.261***
	[27.697]	[27.412]	[20.536]	[20.747]	[47.098]	[47.613]	[36.950]	[41.139]
Δfuel oil price	150.8***	151.2***	201.6***	158.4***	137.5***	140.1***	167.3***	156.560***
	[36.461]	[36.082]	[27.072]	[27.411]	[45.073]	[45.621]	[36.830]	[42.243]
Δwholesale price index (P^w)	0.785***	0.785***	0.837***	0.841***	0.902***	0.897***	0.949***	1.006***
	[0.041]	[0.041]	[0.031]	[0.030]	[0.065]	[0.065]	[0.053]	[0.053]
θ_I	0.603***	0.601***	0.212***	0.198***	0.380**	0.396**	0.168**	-0.050
	[0.131]	[0.130]	[0.051]	[0.066]	[0.167]	[0.170]	[0.070]	[0.090]
θ_G	-.00009***	-.00009***	-.00006***		-.00009***	-.00009***	-.00006***	
	[0.00002]	[0.00002]	[0.00001]		[0.00002]	[0.00002]	[0.00002]	
θ_T	-0.034***	-0.034***		-0.015**	-0.017	-0.018		0.004
	[0.010]	[0.010]		[0.007]	[0.012]	[0.012]		[0.009]
constant	-381.1***	-381.8***	-334.9***	-177.8***	-445.8***	-451.3***	-379.4***	-147.110
	[86.426]	[85.511]	[69.863]	[54.712]	[139.979]	[141.482]	[126.413]	[99.302]
Observations	210	210	210	210	84	84	84	84
R-squared	0.79	0.81	0.86	0.88	0.89	0.89	0.90	0.90
Breusch-Pagan test for heteroscedasticity (p-value)	0.74		0.77	0.60	0.28		0.29	0.22
Wooldridge test for autocorrelation (p-value)	0.70		0.54	0.59	0.22		0.22	0.03
Durbin-Watson		1.74				2.21		

Table 2.2 (continued)

Variables	Full sample				Main growing area			
	I3SLS	N3SLS	I3SLS	I3SLS	I3SLS	N3SLS	I3SLS	I3SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Supply equation, dependent variable: Jasmine rice supply (ΔQ)								
Δfarm gate price (P^f)	0.051***	0.054***	0.056***	0.055***	0.071***	0.090***	0.062***	0.050**
	[0.014]	[0.014]	[0.014]	[0.014]	[0.021]	[0.022]	[0.022]	[0.023]
Δfertilizer price ($ferp$)	0.865***	0.913***	0.676**	0.677**	1.448**	1.476**	1.640***	2.030***
	[0.289]	[0.291]	[0.286]	[0.287]	[0.587]	[0.600]	[0.585]	[0.594]
Δfarm gate price*fertilizer price ($P^f * ferp$)	-.00005***	-.00006***	-.00005***	-.00005***	-.00009***	-.0001***	-.00009***	-.000***
Δlagged rain in quarter 3	2.000***	1.987***	2.050***	1.967***	2.060*	2.164*	2.033*	2.137**
	[0.693]	[0.699]	[0.681]	[0.687]	[1.074]	[1.115]	[1.059]	[1.038]
Δ(lagged rain in quarter 3)^2	-0.007***	-0.007***	-0.007***	-0.007***	-0.007**	-0.007**	-0.007**	-0.007**
	[0.00001]	[0.00001]	[0.00001]	[0.00001]	[0.00003]	[0.00003]	[0.00003]	[0.000]
constant	-24.570*	-25.593*	-24.702*	-25.258*	-35.348*	-41.137**	-33.909*	-29.503
	[13.259]	[13.365]	[13.162]	[13.235]	[18.150]	[18.527]	[18.332]	[19.046]
R-squared	0.45	0.45	0.44	0.44	0.81	0.82	0.80	0.80
Breusch-Pagan test for heteroscedasticity (p-value)	0.29		0.29	0.29	0.12		0.12	0.12
Wooldridge test for autocorrelation (p-value)	0.08		0.08	0.08	0.45		0.45	0.45
Durbin-Watson		2.18				2.56		

Note: The quantities in blankets below the estimates are the standard errors. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively. We use TSP 5.1 for N3SLS. Standard error of N3SLS estimators is robust to heteroscedasticity. In the supply equation, controls for government policy, rain, the price of other crops and years are not shown. In the perceived demand equation, control for minimum wage is not shown. Full regression results are available in Appendix D1.

Moreover, the positive price spread will also force the rice millers to increase the buying price in order to compete with the government. The θ_T is also statistically significant, and its coefficient implies an approximate 0.034 decrease in oligopsony power per year, on average. In addition, the coefficient of constant oligopsony power (θ_I) is positive and highly statistically significant.

Following the NEIO literature, column 2 uses nonlinear three-stage least squares (N3SLS) to estimate supply and derived demand equation. The results are similar to column 1, where we use iterative three-stage least squares (I3SLS). Thus, allowing for nonlinear parameters makes no difference in our regression model. To perform robustness checks, column 3 drops θ_T from oligopsony power components. Dropping θ_T reduces the coefficient on other oligopsony power components, yet they remain highly statistically significant. Column 4 drops θ_G from oligopsony power components. The results are similar to dropping θ_T. Columns 5-8 estimate parallel specification but with the main growing area sample. The results are generally similar, except that the coefficient on θ_T becomes statistically insignificant in columns 5 and 6. In addition, in column 8, the coefficient on θ_I and θ_T turn statistically insignificant. These misleading results may arise from misspecification. We suspect that dropping θ_G leads to serial correlation in the derived demand equation. The remaining results of the perceived demand equation and supply equation have reasonable effects. For example, an increase in output price (wholesale price index) has a strongly positive effect on the price of input (farm gate price) and rain has a diminishing effect on rice supply (see Appendix D for further discussion).

Table 2.3 summarizes the estimates of oligopsony power in each specification. The estimates of θ in the full sample and main growing area sample range from -0.39 to 0.65 and -0.21 to 0.55, respectively.[23]

[23] Although the negative values of θ are not theoretically possible, they arise because the simple specification (2.9) does not constrain θ to be nonnegative. Our interpretation is that during this period intermediaries do not have oligopsony power.

Table 2.3 Estimates of oligopsony power (θ) for selected marketing year and the value for calculating the oligopsony power

Marketing year	Full sample					Main growing area				
	Oligopsony power model									
	(1)	(2)	(3)	(4)	$pdif\ govmar_t$	(5)	(6)	(7)	$pdif\ govmar_t$	$ttrend$
2002/03	0.40	0.40	0.13	0.17	1,384	0.25	0.27	0.08	1,403	2
2003/04	0.65	0.65	0.31	0.15	-1,522	0.53	0.55	0.28	-1,695	3
2004/05	0.16	0.16	0.02	0.14	3,111	0.12	0.13	-0.02	2,874	4
2005/06	0.12	0.12	0.02	0.12	3,104	0.13	0.14	-0.01	2,728	5
2006/07	0.28	0.28	0.14	0.11	1,188	0.27	0.29	0.09	1,169	6
2007/08	0.40	0.40	0.24	0.10	-363	0.42	0.43	0.20	-412	7
2008/09	0.04	0.04	0.03	0.08	2,886	0.18	0.20	0.02	2,163	8
2009/10	0.29	0.29	0.21	0.07	0	0.38	0.40	0.17	0	9
2010/11	0.26	0.26	0.21	0.05	0	0.38	0.40	0.17	0	10
2011/12	-0.25	-0.25	-0.09	0.04	4,808	-0.04	-0.03	-0.14	4,594	11
2012/13	-0.29	-0.29	-0.09	0.02	4,818	-0.03	-0.03	-0.14	4,578	12
2013/14	-0.39	-0.39	-0.13	0.01	5,497	-0.13	-0.13	-0.21	5,667	13
2014/15	0.12	0.12	0.21	-0.01	0	0.38	0.40	0.17	0	14
2015/16	0.09	0.09	0.21	-0.02	0	0.38	0.40	0.17	0	15

Note: $\theta = \theta_I + \theta_G pdif govmar_t + \theta_T ttrend$

The fluctuation in oligopsony power reflects the change in government support prices. For example, the oligopsony power went from 0.4 in 2007/08 to 0.04 in 2008/09 because[24] the new civilian government[25] significantly increased the level of support price from \$260 to \$419 per ton, or an increase of approximately 61%. Next, as the price elasticity of rice supply is approximately 1 (see Table E1 in Appendix E), the oligopsony price distortion is close to the estimated oligopsony power. The estimated oligopsony price distortions in the full sample and main growing area sample range from -33% to 55% and -18% to 47%, respectively (see Table E2 in Appendix E). Overall, the results in Tables 2.2 , 2.3 and E2 show the evidence of some oligopsony power, oligopsony price distortion, and a negative relationship between price support and oligopsony power.

2.7 Policy Implication

To use the results of the previous section in evaluating the PPP, estimates of the management costs of the PPP and release rice price data are required. The estimated management costs and release Jasmine rice price are reported in Appendix F. In short, the management cost that we use for our cost estimation is \$57.4 per ton, and we assume the release rice price is 17% lower than the market price. Another consideration is the accuracy of the model prediction. In the supply equation and derived demand equation (column 5), $R^2 = 0.81$ and 0.89, respectively. These high *R*-squares mean that we can precisely evaluate the welfare effect of the PPP. Thus, we evaluate the welfare effect of the PPP using a regression model from the main growing area sample which accounts for 68% of total government purchase.

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[24] The referee points out that such a sharp change might also imply the breakdown of the collusion agreement in a dynamic setting. If this was the case, the model estimates might be biased.

[25] Thailand returned to civilian rule in 2008 after 2 years of military rule (military leaders staged a coup in 2006).

2.7.1 Market and welfare effects of the paddy pledging program

Figure 2.3 presents Thailand's Jasmine rice market during the implementation of the PPP. We estimate the values in Figure 2.3 using the sample mean value and calculation procedure in 2.4.2.

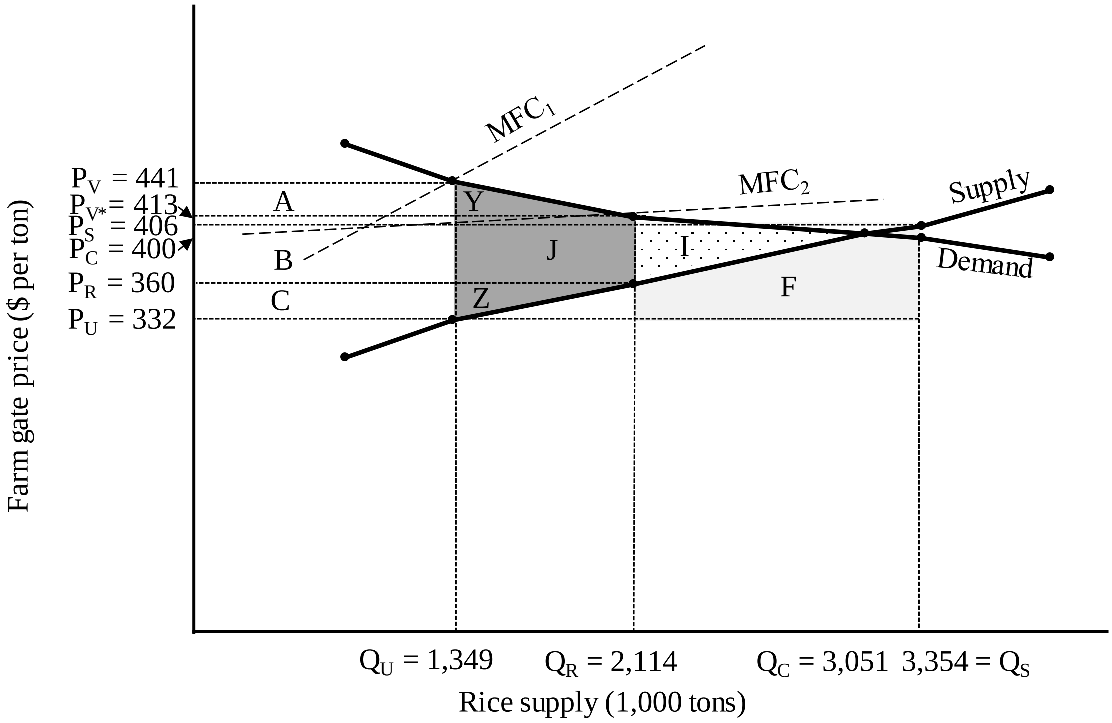

Figure 2.3 The Thai Jasmine rice market during the implementation of the paddy pledging program.

Note: The original values are computed in Thai Baht, but to facilitate interpretation they are converted into U.S. dollars at the fixed exchange rate of 35.8 baht per dollar.

We find that the PPP increases both farmers' and consumers' gains by cutting the oligopsony margins of intermediaries. Consistent with empirical findings in U.S. dairy markets (Chavas and Kim, 2004), price support generates an 8% increase in farm gate price. As a result, the program decreases the margin of rice millers from \$109 to \$53 per ton. Consequently, consumers and farmers each gain \$10.6 million per year (areas Y and Z).

However, we find the paddy pledging program to be inefficient. The program increases consumer surplus (Y), producer surplus (Z+I), and processor surplus (J) around \$10.6 million, \$38.8 million, and \$40.5 million, respectively. The government pays for the buying cost and management cost \$449.6 million and \$70.6 million, respectively. As the revenue from rice releasing is \$445.3 million, the net cost of the program is \$124.9 million. Since the program increases surplus by only $90.0 million (Y+Z+I+J), it imposes a deadweight loss to society of about $34.9 million per year. Next, we consider the income redistribution effect of the program. We find the program to be effective in income redistribution. Under the program, consumer's surplus (A) and producer's surplus (C) equally increase by $37.4 million. Thus, the total surplus transfer from intermediaries (oligopsony profits) to consumers and producers is $74.8 million. In addition, the government also transfers an income from taxpayers to farmers of about $62.4 million (F). Therefore, the program redistributes an income from intermediaries and taxpayers to farmers and consumers of around $137.2 million per year. As the net cost of the program is $124.9 million, every public dollar spent on the PPP returns $1.10 in income redistribution.

2.7.2 Price support design in the presence of oligopsony power

Figure 2.4 shows the Thai Jasmine rice market under complete deregulation. Due to the intermediary's oligopsony power, farmers lose a surplus $91.2 million per year (L) and $59.7 million per year (M).

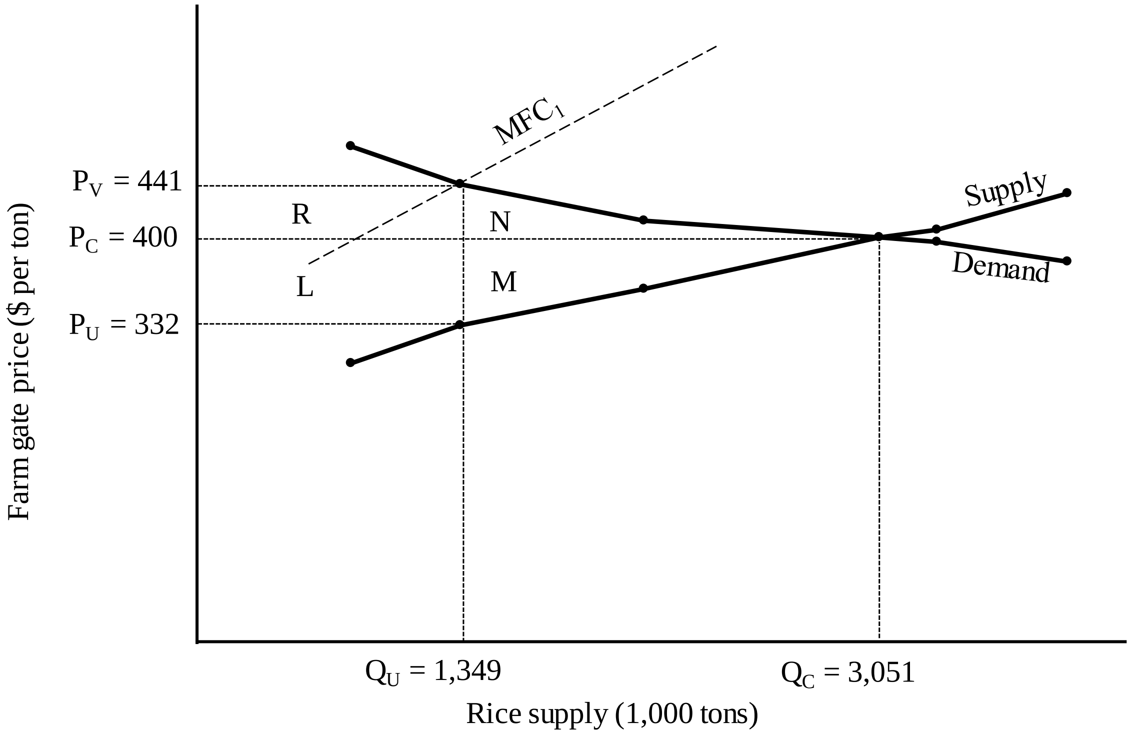

Figure 2.4 The Thai Jasmine rice market without government intervention.

Consumers also lose a surplus $55.2 million per year (R) and $26.8 million per year (N). In contrast, intermediaries gain a surplus $146.4 million per year (R+L) by transferring it from farmers and consumers. The government can improve the market outcome by setting the minimum support price between \$332 and \$400 per ton. At this price interval, the government does not have to buy rice from farmers. As a result, total social welfare will increase if decreases in deadweight losses are larger than administrative costs.

2.8 Conclusion

Despite the general concern regarding the existence of oligopsony power in developing countries (Lopez and You, 1993), the importance of oligopsony power in policy evaluation has been ignored. This study is the first to examine the welfare effect of price support policy under imperfect competition in developing countries. In this paper, we develop a rice market model based on the NEIO framework to directly estimate oligopsony power. We also develop an imperfect competition model based on the theoretical work of Russo et al. (2011) to evaluate the welfare effects of the Paddy Pledging Program (PPP), a price support policy in Thailand.

We find strong evidence of some oligopsony power over the MY2002/03 to MY2015/16 sample period. We also find a negative relationship between price support and oligopsony power. Next, although we find the PPP to be inefficient, it is effective in income redistribution. Moreover, the program benefits not only farmers but also consumers, and it can be designed to increase total social welfare by setting the optimal support price. Our findings challenge generally accepted "wisdom" regarding price support policy in agricultural markets. The perceived wisdom regarding this policy is that it benefits farmers, hurts consumers, and always imposes a deadweight loss on society. Therefore, the government should eliminate the price support policy. However, our findings show that in imperfect competition market, price support policy can benefit both farmers and consumers and can be designed to increase social welfare.

Our results also carry important policy implications. The policy prescription to deregulate agricultural markets in developing countries must be undertaken with caution. In an agricultural market with oligopsony power, government policies can be warranted not only to mitigate market distortion but also to protect small farmers and consumers from the adverse effects of market power. While our investigation focused on the Thai Jasmine rice market, it is not clear whether similar results would hold in other markets. In addition, as we use aggregated data, future research using microdata is needed to expand our knowledge of the degree of oligopsony power and its interaction with price support policy in developing countries.

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Appendix

A. A calculation procedure

First, we estimate P_{V^*}, P_V, P_U, Q_U, and P_{S^*} by the following step (see Figure A1).

1. Estimate P_{V^*} from below formula

$$P_{V^*}\ or\ VMP_R = P_R\left(1+\frac{\theta_R}{\varepsilon}\right)$$

where θ_R is oligopsony power under a regulated market or price support program.

2. Estimate P_V and P_U from below formula

$$P_U\left(1+\frac{\theta_U}{\varepsilon}\right) = P_V\ or\ VMP_U$$

where θ_U is oligopsony power under unregulated market or no price support program.

Since we have $\left(1+\frac{\theta_U}{\varepsilon}\right)$, P_{V^*}, and P_R, we can obtain P_V and P_U by decreasing P_R by 1 unit and increasing P_{V^*} by 1 unit (see Figure A1) until we find the gap between P_R and P_{V^*} that equal $\left(1+\frac{\theta_U}{\varepsilon}\right)$.

3. To get Q_U,

3.1 Solve for predicted Δsupply equation by substituting the average value of each variable into estimated supply equation (7), we have

$$\widehat{\Delta Q} = d\widehat{\Delta P} + e \qquad (1)$$

where d and e are a number.

3.2 Calculate the change in price (ΔP) from the unregulated market (P_U) to the regulated market (P_R), $\Delta P = P_U - P_R$

3.3 Plug ΔP into predicted Δsupply equation (1), we get the estimated change in supply under unregulated market ($\widehat{\Delta Q_U}$).

3.4 Since we know the actual supply (Q_R) and actual supply change (ΔQ_R) under the regulated market, we can estimate Q_U from $Q_U = Q_R + (\widehat{\Delta Q_U} - \widehat{\Delta Q_R})$

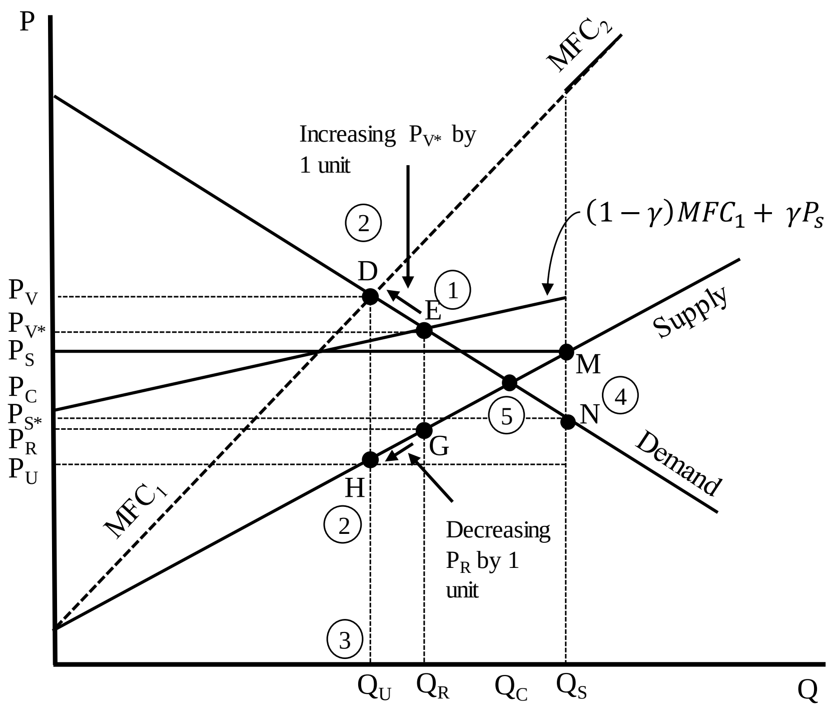

Figure A1 A calculation procedure for welfare analysis

Note: the number enclosed within a circle symbol is the number of the procedure to be calculated

4. To get P_{S*},

   4.1 Solve for predicted Δderived demand equation based on the change in rice supply (ΔQ) by,

      4.1.1 Our estimated predicted derived demand equation is $\widehat{\Delta P} = -\theta\widehat{\Delta Q}^* + c$ where c is a number and $\widehat{\Delta Q}^* = \frac{\widehat{\Delta Q}}{\alpha_1+\alpha_3 * ferp_{t-1}}$

      Multiply above equation by $h = \alpha_2 + \alpha_3 * ferpy$, we have $h\widehat{\Delta P} = -\theta\widehat{\Delta Q} + hc$

      4.1.2 Plug average value of each variable into estimated derived demand equation (9), we have predicted change in price ($\widehat{\Delta P}$)

      4.1.3 Since we know h, $\Delta P, -\theta,$ and ΔQ, we can get c from $c = (h\widehat{\Delta P} - (-\theta\widehat{\Delta Q}))/h$

      4.1.4 Now we have c value; we can plug c value into the predicted derived demand equation

$$h\widehat{\Delta P} = -\theta\widehat{\Delta Q} + hc \qquad (2)$$

4.2 As we observed Q_R , we can estimate the change of supply at point P_{S*} from $\Delta Q_s = Q_S - Q_R$. Since Q_S equal Q_R + the amount of government rice purchase, we have ΔQ_s = the amount of government rice purchase

4.3 Plug ΔQ_s in predicted Δderived demand equation (2), we get the estimated change in price ($\widehat{\Delta P_{S*}}$)

4.4 Since we have estimated price (P_{V*}) and estimated change in price (ΔP_{V*}) in predicted demand equation, we can estimate P_{S*} from $P_{S*} = P_{V*} + (\widehat{\Delta P_{S*}} - \widehat{\Delta P_{V*}})$

5. So far, we have point D, E, and N on derived demand curve and point H, G, and M in supply curve (see Figure A1). To get competitive equilibrium (P_C, Q_C),

5.1 Solve for linear approximation of derived demand and supply based on point D, E, N and H,G,M, we have

$$Q_{de} = gP + n \text{ ... Derived demand equation}$$

$$Q_{su} = mP + v \text{ .... Supply equation}$$

where *g, m, n,* and *v* are number.

5.2 Solve derived demand equation and supply equation; we have P_C and Q_C

B. Detail on variables

The Jasmine paddy supplied variable used in the estimation is constructed by subtracting Jasmine paddy production by the amount of Jasmine paddy purchased by the government, the amount of household consumption and the amount of seed used. The amount of household consumption is estimated by multiplying the number of Jasmine rice farming household by household size and per capita rice consumption. The amount of seed used is calculated by multiplying the planted area by seed rate used per unit of area. The government Jasmine paddy purchased data are from Department of Internal Trade (2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2012, 2013, 2014) , Ministry of Commerce. The Jasmine paddy rice production, Jasmine rice farming household, household size, planted area and seed rate data are from Agricultural Data Operation Center by Office of Agricultural Economics (2015, 2017a, 2017b), Ministry of Agriculture and Cooperatives, which complies crop production data, farm gate price data and agricultural farm household socio-economic data from relevant government agencies. The per capita rice consumption is drawn from Production, Supply and Distribution Database by United States Department of Agriculture (USDA)[26].

In considering the effect of government support price policy on oligopsony power, we construct the price difference variable by subtracting the government support price by the market price during the harvesting time. Moreover, to capture the effect of government support price on rice supply, we construct the dummy variable of government support price by comparing the government support price with the market price. This variable equals 1 if government support price is 20%[27] higher than market price and 0 otherwise. The government Jasmine paddy support price data are from Department of Internal Trade. The data of Jasmine farm gate price are from Office of Agricultural Economics (2017c).

Rainfall variables are constructed by multiplying rainfall data with the percentage of Jasmine rice planted area to total rice planted area[28]. Rainfall data are from Climatic Data Service Center by the Thai Meteorological Department (2017), Ministry of Digital Economy and Society. Rice planted area data are from Office of Agricultural Economics. Fertilizer price variable is constructed by dividing fertilizer imported value by imported quantity[29]. The data on import is from Thailand's Trading Database by Ministry of Commerce (2017).

Ideally, one would like to use actual electricity price data to reflect the energy cost of rice milling. However, unfortunately, this data is unavailable. Thus, we use the fuel oil price as a proxy variable for electricity price. Fuel oil price is a good proxy since it is used as a reference price for natural gas which accounts for 69% of total supply resources used to generate electricity in Thailand in 2015 (Electricity Generating Authority of Thailand., 2015). Besides, electricity price is generally set on a cost-plus basis. Therefore, fuel oil price is correlated with

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[26] Available at https://apps.fas.usda.gov/psdonline/app/index.html#/app/advQuery

[27] The mean value of the percentage price difference between government support price and market price in the sample

[28] Weight is used to make the effect of rain variable on Jasmine rice production more precise.

[29] This fertilizer price is a reasonable choice because nearly 100% of fertilizer used in Thailand is imported fertilizer (Chitibut, Poapongsakorn, & Aroonkong, 2014).

electricity price. Fuel oil price data are from Real Sector Statistics by Bank of Thailand[30].

The wholesale Jasmine rice price index variable is calculated based on Jasmine rice milling conversion rate and wholesale Jasmine milled rice price and its by product price in Bangkok. These data are from Department of Internal Trade (2017a, 2017b, 2017c, 2017d). Thai population variable and exchange rate variable are used as instrumental variables for the endogenously determined wholesale Jasmine rice price index. Thai population data are from Department of Provincial Administration (2017), and the exchange rate is from Bank of Thailand[31]. All price and income variables were deflated using the consumer price index from Bureau of Trade and Economic Indices (2017).

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[30] Available at http://www2.bot.or.th/statistics/BOTWEBSTAT.aspx?reportID=90&language=ENG

[31] Available at http://www2.bot.or.th/statistics/BOTWEBSTAT.aspx?reportID=123&language=ENG

C. Unit root test

Table C1 Harris-Tzavalis unit-root test for all variables included in the analysis.

Variables	P-value	
	levels	first differences
jasmine paddy production	0.0000	0.0000
farm gate price	1.0000	0.0000
fertilizer price	0.0011	0.0000
farm gate price*fertilizer price	0.0101	0.0000
lagged rain in quarter 3	0.0000	0.0000
(lagged rain in quarter 3)^2	0.0000	0.0000
lagged rain in October	0.0000	0.0000
(lagged rain in October)^2	0.0000	0.0000
lagged sugarcane farm gate price	0.0753	0.0000
lagged cassava farm gate price	0.0000	0.0000
lagged minimum wage	0.9998	0.0188
lagged farm gate price in quarter 2	0.0037	0.0000
diesel price	0.9470	0.0000
minimum wage	0.9953	0.0160
fuel oil price	1.0000	0.0000
wholesale price index	0.9978	0.0000
Thai population	0.0235	0.0000
Exchange rate Thai baht to Dollar	1.0000	0.0001

Note: Ho: Panels contain unit roots, Ha: Panels are stationary

Table C2 Cointegration test between price variables in derived demand equation.

Cointegration test	P-value
Westerlund test	
Variance ratio	0.1321
Pedroni test	
Modified Phillips-Perron t	0.0364
Phillips-Perron t	0.0000
Augmented Dickey-Fuller t	0.0000

Note Ho: No cointegration. Ha: All panels are cointegrated.

D. The detail discussion of the remaining results

The remaining results of the perceived demand equation have reasonable effects (see Table D1). An increase in output price (wholesale price index) has a strongly positive effect on the price of input (farm gate price). The proxy variable for electricity price (fuel oil price) is also very statistically significant. Although it seems counterintuitive that the farm gate price increases if energy price[32] increases, it may be that an increase in electricity price causes an increase in demand for paddy rice. This situation may arise because an increase in the processing scale will reduce per unit-processing cost. The coefficient on the minimum wage is small and very insignificant. This reflects the fact that rice milling is capital intensive. As the rice millers sell milled rice nationwide, the coefficient on diesel price variable is statistically significant and has a negative effect on the farm gate price. As the Breusch-Pagan test for heteroscedasticity and Wooldridge test for autocorrelation result in high p-value, our derived demand equation has no heteroskedasticity and autocorrelation problem.

The results of the supply equation have the expected effects. The farm gate price variable, the fertilizer price variable, and their interaction are statistically significant at the 1% significance level. Counterintuitively, from the mean value of Δfarm gate price, one bath increase in fertilizer price increases rice supply by 853 tons. This may be the case because of the government fertilizer subsidy program. Next, the coefficient on price support dummy is negative and statistically significant. If the government set a price 20% higher than the market price, the rice supply available in the market will decrease by 55,000 tons, an expected result. Like derived demand equation, our supply equation has no heteroskedasticity and autocorrelation problem.

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[32] Which represents the cost of processors

Table D1 I3SLS and N3SLS estimations of perceived demand equation and supply equation

Variables	Full sample				Main growing area			
	I3SLS (1)	N3SLS (2)	I3SLS (3)	I3SLS (4)	I3SLS (5)	N3SLS (6)	I3SLS (7)	I3SLS (8)
Perceived demand equation, dependent variable: farm gate price (ΔP)								
Δdiesel price	-70.5**	-70.0**	-112.0***	-82.1***	-66.8	-68.2	-102.5***	-123.261***
	[27.697]	[27.412]	[20.536]	[20.747]	[47.098]	[47.613]	[36.950]	[41.139]
Δminimum wage	-1.023	-0.874	1.913	4.191	-5.11	-5.64	-3.410	-1.546
	[3.659]	[3.622]	[2.835]	[2.562]	[4.788]	[4.844]	[4.443]	[4.456]
Δfuel oil price	150.8***	151.2***	201.6***	158.4***	137.5***	140.1***	167.3***	156.560***
	[36.461]	[36.082]	[27.072]	[27.411]	[45.073]	[45.621]	[36.830]	[42.243]
Δwholesale price index	0.785***	0.785***	0.837***	0.841***	0.902***	0.897***	0.949***	1.006***
	[0.041]	[0.041]	[0.031]	[0.030]	[0.065]	[0.065]	[0.053]	[0.053]
θ_I	0.603***	0.601***	0.212***	0.198***	0.380**	0.396**	0.168**	-0.050
	[0.131]	[0.130]	[0.051]	[0.066]	[0.167]	[0.170]	[0.070]	[0.090]
θ_G	-.00009***	-.00009***	-.00006***		-.00009***	-.00009***	-.00006***	
	[0.00002]	[0.00002]	[0.00001]		[0.00002]	[0.00002]	[0.00002]	
θ_T	-0.034***	-0.034***		-0.015**	-0.017	-0.018		0.004
	[0.010]	[0.010]		[0.007]	[0.012]	[0.012]		[0.009]
Δconstant	-381.1***	-381.8***	-334.9***	-177.8***	-445.8***	-451.3***	-379.4***	-147.110
	[86.426]	[85.511]	[69.863]	[54.712]	[139.979]	[141.482]	[126.413]	[99.302]
Observations	210	210	210	210	84	84	84	84
R-squared	0.79	0.81	0.86	0.88	0.89	0.89	0.90	0.90
Breusch-Pagan test for heteroscedasticity	0.74		0.77	0.60	0.28		0.29	0.22
Wooldridge test for autocorrelation	0.70		0.54	0.59	0.22		0.22	0.03
Durbin-Watson		1.74				2.21		

Table D1 (continued)

Variables	Full sample				Main growing area			
	I3SLS	N3SLS	I3SLS	I3SLS	I3SLS	N3SLS	I3SLS	I3SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Supply equation, dependent variable: jasmine rice supply (ΔQ)								
Δfarm gate price	0.051***	0.054***	0.056***	0.055***	0.071***	0.090***	0.062***	0.050**
Δfertilizer price	0.865***	0.913***	0.676**	0.677**	1.448**	1.476**	1.640***	2.030***
	[0.289]	[0.291]	[0.286]	[0.287]	[0.587]	[0.600]	[0.585]	[0.594]
Δfarm gate price*fertilizer price	-.00005***	-.00006***	-.00005***	-.00005***	-.00009***	-.0001***	-.00009***	-.000***
	[0.00001]	[0.00001]	[0.00001]	[0.00001]	[0.00003]	[0.00003]	[0.00003]	[0.000]
Δprice support dummy	-55.618***	-55.063***	-42.381**	-38.354**	-212.3***	-192.6***	-233.1***	-283.2***
	[18.790]	[18.940]	[18.661]	[18.725]	[27.808]	[28.219]	[27.971]	[27.695]
Δlagged rain in quarter 3	2.000***	1.987***	2.050***	1.967***	2.060*	2.164*	2.033*	2.137**
	[0.693]	[0.699]	[0.681]	[0.687]	[1.074]	[1.115]	[1.059]	[1.038]
Δ(lagged rain in quarter 3)^2	-0.007***	-0.007***	-0.007***	-0.007***	-0.007**	-0.007**	-0.007**	-0.007**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]	[0.003]	[0.003]
Δlagged rain in October	1.273***	1.278***	1.161***	1.186***	2.508***	2.513***	2.518***	2.482***
	[0.406]	[0.409]	[0.401]	[0.404]	[0.497]	[0.515]	[0.491]	[0.484]
Δ(lagged rain in October)^2	-0.003**	-0.003**	-0.003**	-0.003**	-0.007***	-0.007***	-0.007***	-0.007***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]
Δlagged sugarcane farm gate price	0.194	-0.026	0.356**	0.319*	-0.363	-0.092	-0.583**	-0.910***
	[0. [illegible]	[0. [illegible]	[0. [illegible]	[0. [illegible]	[illegible]	[0.[illegible]	[0.[illegible]	[0.[illegible]
Δlagged cassava farm gate price	-0.[illegible]	0.[illegible]	0.[illegible]	-0.[illegible]	[illegible]	-0.[illegible]	-0.1[illegible]	-0.2[illegible]
	[0.052]	[0.179]	[0.052]	[0.052]	[0.078]	[0.292]	[0.077]	[0.079]
Δlagged minimum wage	-0.383	-0.346	-0.338	-0.422	-0.868	-0.668	-0.982*	-0.984*
	[0.386]	[0.389]	[0.380]	[0.383]	[0.565]	[0.585]	[0.559]	[0.555]
Δlagged farm gate price in quarter 2	0.016*	0.015	0.023**	0.021**	0.017	0.029**	0.006	-0.011
	[0.009]	[0.009]	[0.009]	[0.009]	[0.013]	[0.013]	[0.013]	[0.013]

Table D1 (continued)

Variables	Full sample				Main growing area			
	I3SLS (1)	N3SLS (2)	I3SLS (3)	I3SLS (4)	I3SLS (5)	N3SLS (6)	I3SLS (7)	I3SLS (8)
Year 2010	-23.754	-19.916	-116.545	-105.569	156.619	13.979	285.048**	477.742***
	[76.517]	[77.167]	[75.409]	[76.025]	[119.698]	[122.893]	[119.128]	[121.048]
Year 2011	56.160	64.018	-10.873	13.396	306.317**	246.826**	390.373***	500.115***
	[85.744]	[86.453]	[84.771]	[85.364]	[132.735]	[135.899]	[131.520]	[135.652]
Year 2015	247.0***	248.3***	279.4***	298.2***	256.314***	326.307***	198.077**	46.156
	[63.799]	[64.310]	[63.264]	[63.596]	[86.710]	[88.223]	[87.753]	[87.525]
Year 2016	78.023	79.946	127.0***	117.518**	44.017	108.970	-10.739	-87.987
	[49.351]	[49.772]	[48.588]	[49.021]	[70.435]	[72.575]	[69.694]	[70.263]
Δconstant	-24.570*	-25.593*	-24.702*	-25.258*	-35.348*	-41.137**	-33.909*	-29.503
	[13.259]	[13.365]	[13.162]	[13.235]	[18.150]	[18.527]	[18.332]	[19.046]
R-squared	0.45	0.45	0.44	0.44	0.81	0.82	0.80	0.80
Breusch-Pagan test for heteroskedasticity	0.29		0.29	0.29	0.12		0.12	0.12
Wooldridge test for autocorrelation	0.08		0.08	0.08	0.45		0.45	0.45
Durbin-Watson		2.18				2.56		

Note: The quantities in blankets below the estimates are the standard errors. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively. We use TSP 5.1 for N3SLS. The standard error of N3SLS estimators is robust to heteroskedasticity.

E. Oligopsony price distortion

We need to estimate the price elasticity of rice supply (ε) so that we can estimate oligopsony price distortion. Table E1 shows that Jasmine rice supply is price elastic. The coefficient of Δlog(farm gate price) is the estimated elasticity of rice supply with respect to price. The estimated results in column 1 imply that a 1% increase in the farm gate price increases the rice supply by about 1.18%. Column 2 drops rain variables. This causes the coefficient on Δlog(farm gate price) to slightly decrease. Column 3 and 4 estimate parallel specification but with the main growing area sample. The results are generally similar. Overall, the results in Table E1 shows that our estimated price elasticity of rice supply is elastic and robust across model specifications.

Table E1 2SLS estimations of supply equation. Dependent variable: Log (Jasmine rice supply)

Variables	Full sample		Main growing area	
	(1)	(2)	(3)	(4)
Δlog (farm gate price)	1.183***	1.128***	1.164***	1.139***
	[0.265]	[0.249]	[0.333]	[0.340]
Δfertilizer price	0.000	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Δgovernment support price	-0.000**	-0.000*	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Δlagged rain in quarter 3	0.004		-0.000	
	[0.003]		[0.006]	
Δ(lagged rain in quarter 3)^2	-0.000		0.000	
	[0.000]		[0.000]	
Δlagged rain in October	0.005**		0.006***	
	[0.002]		[0.002]	
Δ(lagged rain in October)^2	-0.000*		-0.000**	
	[0.000]		[0.000]	
Observations	210	210	84	84
R-square	0.391	0.362	0.647	0.602

Note: The quantities in blankets below the estimates are the robust standard errors. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively. Each regression also includes lagged farm gate price of the competitive crop, lagged minimum wage, and year dummy variables when there is no rice pledging policy.

Table E2 presents the estimates of oligopsony price distortion according to the specification of the oligopsony power component. As the price elasticity of rice supply is around 1, the oligopsony price distortion is close to the estimated oligopsony power. The estimate of oligopsony price distortion in the full sample and main growing area sample range from -33% to 55% and -18% to 47%, respectively.

Table E2 Estimates of oligopsony price distortion for selected marketing year

Marketing year	Full sample				Main growing area		
	Oligopsony power model						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2002/03	0.34	0.34	0.11	0.14	0.21	0.23	0.07
2003/04	0.55	0.55	0.26	0.13	0.46	0.47	0.24
2004/05	0.14	0.14	0.02	0.12	0.10	0.11	-0.02
2005/06	0.10	0.10	0.02	0.10	0.11	0.12	-0.01
2006/07	0.24	0.24	0.12	0.09	0.23	0.25	0.08
2007/08	0.34	0.34	0.20	0.08	0.36	0.37	0.17
2008/09	0.03	0.03	0.03	0.07	0.15	0.17	0.02
2009/10	0.25	0.25	0.18	0.06	0.33	0.34	0.15
2010/11	0.22	0.22	0.18	0.04	0.33	0.34	0.15
2011/12	-0.21	-0.21	-0.08	0.03	-0.03	-0.03	-0.12
2012/13	-0.25	-0.25	-0.08	0.02	-0.03	-0.03	-0.12
2013/14	-0.33	-0.33	-0.11	0.01	-0.11	-0.11	-0.18
2014/15	0.10	0.10	0.18	-0.01	0.33	0.34	0.15
2015/16	0.08	0.08	0.18	-0.02	0.33	0.34	0.15

F. Management cost and rice price release under the PPP

To evaluating the paddy pledging policy, estimates of the management costs of the PPP are required. The estimates of Siamwalla, Poapongsakorn, and Pantakua (2014) and Poapongsakorn and Charuphong (2010) are used for that purpose. Those studies comprehensively estimate the management cost of the program. Table F1 shows the estimated management cost of the PPP. Column 1 and 2 show that the average management cost per tonne of the paddy pledging program in MY2005/06 and MY2011/12-MY2013/14 is $44.9 and $67.5, respectively. Based on these numbers, we calculate the weighted average management cost of the paddy pledging program during our study period[33]. The weighted average management cost is $57.4 per tonne (column 3). We use this management cost for our cost estimation. In addition, we also need release rice price data to estimate the government's revenue. Poapongsakorn and Wichitaksorn (2016) show that the lowest released rice price of Jasmine milled rice in MY2011/12-MY2013/14 through government to government and auction is 31% and 17% lower than the market price, respectively. In our study, we assume the release rice price is 17% lower than the market price. Table F2 show that average acquisition and release price of Jasmine rice are $406.0 and $361.9 per tonne, respectively.

Table F1 Management cost of the paddy pledging program

Cost items Unit: $ per tonne	MY2005/06[a]	MY2011/12 – MY2013/14[b]	MY2002/03-MY2008/09 and MY2011/12-MY2013/14
Processing cost + Sack cost + Transportation cost	16.9	24.5	21.1
Storage cost	6.7	5.8	6.2
Operating cost	4.0	9.4	7.0
Interest cost	13.1	18.5	16.1
Quality depreciation cost	4.3	9.3	7.1
Total cost	44.9	67.5	57.4

Source: [a]Poapongsakorn and Charuphong (2010) [b]Siamwalla, Poapongsakorn, and Pantakua (2014)
Note: all costs are deflated using CPI.

[33] The weighted average cost is equal [column 1*the proportion of Jasmine paddy bought by the government between MY2002/03-MY2008/09 + column 2* the proportion of Jasmine paddy bought by the government between MY2011/12-MY2013/14]

Table F2 Acquisition and release price of Jasmine rice

Marketing year	Acquisition price* ($ per tonne of paddy)	Release price** ($ per tonne of paddy)
2002/03	262.7	301.3
2003/04	266.0	309.2
2004/05	369.8	279.3
2005/06	349.2	285.2
2006/07	304.0	297.2
2007/08	303.6	415.1
2008/09	486.3	438.2
2011/12	588.5	439.9
2012/13	570.0	449.2
2013/14	559.6	404.6
Average	406.0	361.9

Source: * Department of Internal Trade (2016), Isvilanonda (2010), Poapongsakorn (2010); **Authors' calculation based on data from Department of Internal Trade (2017a, 2017b, 2017c, 2017d) and Poapongsakorn and Wichitaksorn (2016)

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Chapter 3 The spillover effect of direct competition between marketing cooperatives and private intermediaries: Evidence from the Thai rice value chains

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Abstract

Despite the widespread belief that marketing cooperatives' benefits may extend beyond participating farmers, little is known about the cooperative's effect on nonparticipating farmers. This paper exploits exogenous variation in language spoken at home in Thailand to obtain the instrumental variable estimates of the spillover effect of marketing cooperatives. We hypothesize that farmers who sell rice to private intermediaries in the area where there is direct competition between marketing cooperatives and private intermediaries (treated areas) are likely to receive a higher price than those who sell rice in other areas. Using household-level data of rice farmers in Thailand in the marketing year 2018/19, we find strong evidence that farmers in treated areas receive 10.9% higher prices from private intermediaries than those in comparison areas. Our results provide crucial implications for food policy debates regarding the role of marketing cooperatives in agri-food value chains. In particular, evaluating the inclusiveness of marketing cooperatives toward poor farmers should not be limited to sampling and analyzing its members only. Failure to consider the spillover effect could lead to substantial underestimation of the impact of marketing cooperatives on societal welfare.

Keywords: Thailand, Jasmine rice, Spillover effect, Marketing cooperatives, Instrumental variable

3.1 Introduction

Recent years have seen an increased interest in the economic impacts of marketing cooperatives on smallholder marketing performance. This attention has re-emerged because of a widespread belief that marketing cooperatives can be an efficient mechanism for overcoming smallholders' marketing constraints that are caused by their small scale and the structural transformation of agri-food value chains (Barham and Chitemi, 2009; Bernard and Spielman, 2009; Saitone et al., 2018; World Bank., 2003). In rice value chains, for example, ongoing trends of "disintermediation" and vertical coordination (contract farming) between midstream actors (e.g., milling companies) and farmers and vertical integration in the agribusiness sector are eliciting farmers' need for horizontal coordination strategies (Ba et al., 2019; Reardon et al., 2014; Soullier et al., 2020). Recent evidence from Vietnam suggests that vertical and horizontal coordination can be encouraged through well-designed policies and that cooperative strategies can successfully enhance the inclusiveness of rice value chain upgrading and increase smallholders' access to modern market channels (Ba et al., 2019).

Given its potential for improving smallholder marketing performance, significant progress has been made in estimating cooperative effects on participating farmers (Grashuis and Su, 2019). However, little is known about the existence and magnitude of the spillover effect or the cooperative effect on nonparticipating farmers. Nevertheless, this knowledge is critical for food policy debates regarding the roles of marketing cooperatives in agri-food value chains since it is well recognized that the presence of marketing cooperatives may force private intermediaries to raise prices paid to nonparticipating farmers (Bernard et al., 2008a; Hanisch et al., 2013; Jardine et al., 2014; Liang and Hendrikse, 2016; Milford, 2012; Sexton, 1990). One reason for this lack of research is that it is very challenging to correctly estimate the spillover effect of marketing cooperatives in non-experimental settings because of the problem of endogeneity.

In this paper, we address the endogeneity issue by using the instrumental variables (IV) approach to estimate the spillover effect of marketing cooperatives in rice value chains in Thailand. The Thai Jasmine rice value chain provides a critical case study because, since 2014, the Thai government has shifted rice policies from direct market intervention to the empowerment of farmer organizations in rice value chains (Poapongsakorn, 2019). Moreover, policymakers from other countries have always been interested in Thai rice policies because of the successful development of the Thai rice industry towards its leading role in the world market and the concomitant potential impact of Thai rice policies on the world rice situation (Sloop and Welcher, 2017).

Our paper tests the hypothesis that nonparticipating farmers or farmers who sell rice to private intermediaries in the areas where there is direct competition between marketing cooperatives and private intermediaries (treated areas) are likely to receive a higher price than those who sell rice in other areas (comparison areas). We use a binary variable to capture the degree to which a given farmer is affected by the presence of marketing cooperatives. The variable value equals one if the farmer sells rice in treated areas and zero if he/she sells rice in comparison areas.

Using price and location to test the above hypothesis is complicated by two critical issues. The first issue is selection bias. Namely, the existence of direct competition between marketing cooperatives and private intermediaries may be partly driven by favorable local area characteristics such as good institutions and favorable farmer characteristics such as their ability. The second issue is omitted variable bias. Although farmers' marketing decision variables may be correlated with selling locations and can significantly affect outcome variables (e.g., prices), we could not control for these variables due to reverse causality. Moreover, we do not observe variables such as farmers' ability that could also affect outcome variables.

This study addresses selection bias and omitted variable bias by using a plausible instrument to aid identification. We use language spoken at home as IV. Our IV strategy relies on the history of village settlement in Thailand. Specifically, farmers in the treated areas are more likely to speak Lao Isan at home, whereas farmers in the comparison areas are more likely to speak other languages at home. Because language spoken at home is virtually randomly assigned to farmers and unlikely to correlate with the error term, a dummy for language spoken at home provides a valid instrument for farmer's locations or treatment status. In other words, our IV operates like a randomized promotion process, that is, farmers receive treatment is partially determined by the language variable (promotion variable) that is "as if" randomly assigned. As the validity of the instrument variable is often called into question in empirical findings, we also investigate the case where there is some correlation between the instrument and unobserved heterogeneity by employing the partial identification strategy of Nevo and Rosen (2012).

Our paper contributes to the literature by, to the best of our knowledge, providing the first empirical evidence of the existence and magnitude of the spillover effect of marketing cooperatives. The paper also contributes to recent literature that studies interventions which may generate spillovers. As the spatial dispersion of agriculture and the presence of high transaction costs could create local economies, implying that interventions on some farmers may generate a wide range of spillover effects (de Janvry et al., 2017), several studies have investigated the spillover effect of agricultural interventions (Burke et al., 2018; Johnson et al., 2006; Minten et al., 2007). However, prior studies on marketing cooperatives have focused only on estimating the effect of cooperatives on members or participating farmers (Bachke, 2019; Barham and Chitemi, 2009; Bernard et al., 2008b; Chagwiza et al., 2016; Fischer and Qaim, 2012; Malvido Perez Carletti et al., 2018; Markelova et al., 2009; Wollni and Zeller, 2007). Moreover, despite the widespread belief that marketing cooperatives' benefits may extend beyond participating farmers, there is no empirical evidence to reject or support it. Therefore, our study fills a gap in the literature by providing empirical evidence of the untested dimension of the economic performance of marketing cooperatives. This evidence has four crucial implications for food policy debates regarding the role of marketing cooperatives in agricultural development. First, evaluating the inclusiveness of marketing cooperatives toward poor farmers should not be limited to sampling and analyzing participating farmers only. Second, prior studies that do not control[34] for the spillover effect of marketing cooperatives may underestimate the effect of marketing cooperatives on participating farmers. Third, the spillover effect needs to be incorporated in the future evaluation of marketing cooperatives' performance. Lastly, the free rider problem is a significant challenge for marketing cooperatives that needs to be addressed.

Our paper also relates to a few studies that investigate the effect of value chain development in the rice industry. Prior studies have investigated the direct effects and inclusiveness of buyer-driven value chain development or contract farming (Ba et al., 2019; Maertens and Vande Velde, 2017; Mishra et al., 2018; Soullier and Moustier, 2018), and producer-driven value chain development or farmer-owned businesses (Abdul-Rahaman and Abdulai, 2019; Hoken and Su, 2018). Unlike prior studies, our study investigates the indirect or spillover effect of farmer organizations. Therefore, this study contributes to the literature by providing evidence of the spillover effect of producer-driven value chain development in the rice industry.

The remainder of the paper is structured as follows. The next section describes the empirical setting. The section following presents the conceptual framework. We then illustrate the estimation strategy and data used in the analysis, followed by estimation results and implications for policy and evaluation. The last section concludes.

[34] For example, studies that compare participating and nonparticipating farmers in the same areas.

3.2 Background

3.2.1 Jasmine rice value chain

Jasmine is a premium quality rice variety in Thailand. It is famous for its floral aroma and cooking texture. As a result, it commands a premium price in both domestic and international markets (Bairagi et al., 2020). In 2016, 1.9 million farm households with average farm size around 2.15 hectares per household grew Jasmine rice, with a total production of about 8.7 million tons (Rice Department, 2016). Approximately half of the production was exported. Figure 3.1 maps the Jasmine rice value chain. Paddy traders, millers, retailers, and exporters are the primary intermediaries that connect individual rice farmers to domestic and international consumers. In this system, small-scale Jasmine rice farms face many marketing disadvantages. These disadvantages include limited economies of scale due to low volumes of paddy to market, low bargaining power vis-à-vis buyers, high transaction costs, variable and heterogeneous quality, and limited ability to meet the high-quality standards demanded by agribusinesses. To reduce the marketing disadvantages of small farm size, Jasmine rice growers organize themselves in farmer organizations as a means to consolidate their marketing operations. As a result, they can benefit from the advantages of economies of scale and can capture more value for their products by integrating forward in the rice value chain, depicted in Figure 3.1 by expanding their operations into paddy trading, processing, and wholesale[35].

[35] They sell paddy rice to millers and exporters, and milled rice to retailers. Some exporters buy husked rice from millers and further whiten and polish it to milled rice; other exporters buy paddy rice from farmers and/or millers and process it into milled rice.

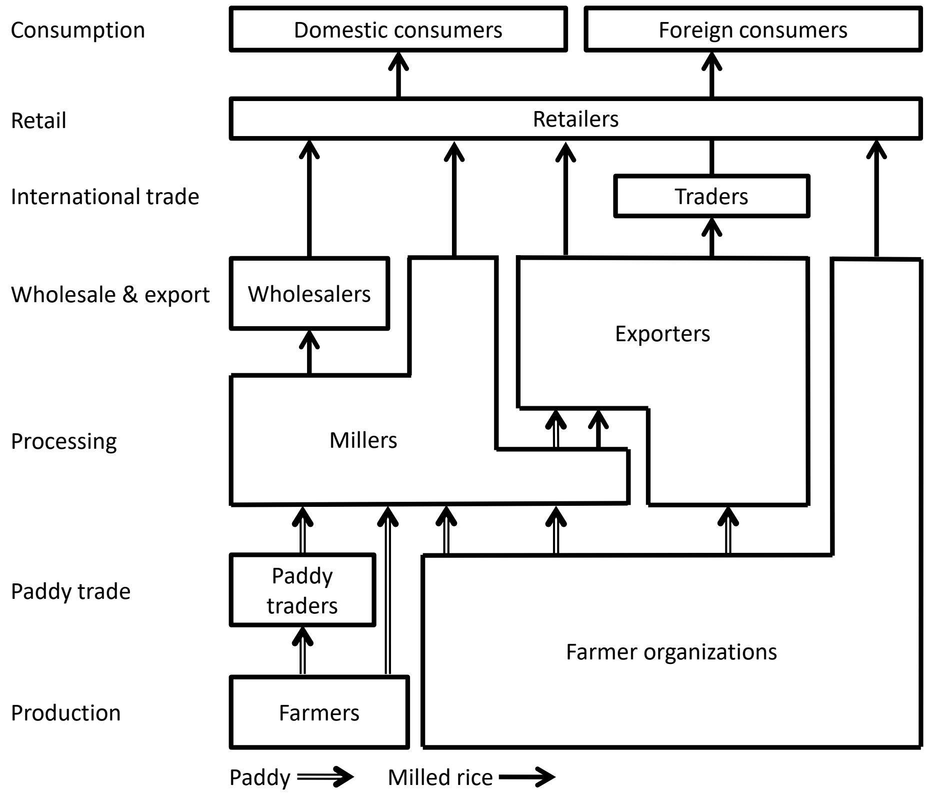

Figure 3.1: Jasmine rice value chain in Thailand
Note: the square areas have no specific meaning.

3.2.2 Treatment and comparison provinces

Our treatment and comparison provinces are Sisaket and Buriram, respectively. These provinces located within the same agro-ecological zone are among the poorest provinces in Thailand (Pawasutipaisit and Townsend, 2011). In 2019, the Agriculture sector accounted for 61% and 78% of the total employment in Buriram and Sisaket, respectively[36](National Statistical Office of Thailand., 2020). The main agricultural products in these two areas are rice, cassava, sugarcane, natural rubber, and onion. Jasmine rice is one of the most popular cash crops grown in these provinces, covering approximately 58% and 67% of the total agricultural land in Buriram and Sisaket, respectively. Table 3.1 shows the macro-provincial level characteristics of Sisaket and Buriram. These provinces have many similar macro characteristics[37] such as per capita income,

[36] Wholesale and retail are the second-largest employment sector, with 13% and 6% of the employment share in Buriram and Sisaket, respectively.

[37] We have no indicator to compare road quality and the quality of local government between Buriram and Sisaket. Alesina and Giuliano (2015) show that culture could affect the quality of institutions, and the quality of institutions matters for various economic outcomes. Given that Buriram and Sisaket have very similar per capita income, we expect no significant difference in road quality, the local government's quality,

road length, the number of rice farming households, average rice farm size, Jasmine rice production, and rice milling capacity.

However, the main difference between these provinces is related to the post-harvest technologies owned by farmer organizations. In particular, farmer organizations in Sisaket have invested in paddy drying technologies, whereas no such investments have taken place in Buriram. Moreover, although the aggregate rice milling capacity in both provinces is similar, the aggregate cooperative milling capacity in Sisaket is almost double Buriram's. These differences are unlikely to occur randomly. Table A in the Appendix shows that 92% of the investment in post-harvest technologies in two areas used outside funding from the special loans or assistance programs. Moreover, the first investment in post-harvest technology in Sisaket took place 17 years earlier than the investment in Buriram. Therefore, the post-harvest technologies' differences are likely to depend on the assistance programs' conditions and other factors such as investment timing.

The difference in post-harvest technology assets (Table 3.1) led farmer organizations to adopt different practices to participate in the Jasmine rice value chain (Figure 3.1) when the Thai government implemented an interest-rate subsidy program for working capital loans for farmer organizations[38] in 2019. In Sisaket, the larger milling and drying capacity of farmer organizations results in the latter directly competing with private intermediaries to buy paddy from farmers as a strategy to fill the capacity and achieve economies of scale. For example, in the marketing year 2018/19[39], the agricultural marketing cooperative formed and operated by the clients of Bank for Agriculture and Agricultural Cooperatives (BAAC)[40] in Sisaket or Sisaket marketing cooperative (SMC)[41] competed with private intermediaries to buy paddy from farmers in some areas within Sisaket.

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and the level of public good provision between the two areas.

[38] Under this program, farmer organizations can borrow money from Bank for Agriculture and Agricultural Cooperatives to buy paddy from members and non-members. Farmer organizations pay only a one percent interest rate; the rest is subsidized by the government.

[39] Note: we define marketing year 2018/19 as November 1, 2018 to October 31, 2019.

[40] BAAC, the largest rural development bank in Thailand, has implemented agricultural value chain intervention by encouraging its clients to form marketing cooperatives since 1989.

[41] SMC was formed in 1991 and represents 136,088 farmers. The SMC has engaged in the processing and marketing of Jasmine rice since 2006 by investing in a rice milling factory with a milling capacity of 80 tons per day. In 2016, it also invested in a rice drying factory with a drying capacity of 300 tons per day. The SMC markets its milled rice under the “A-rice” brand.

Table 3.1: Macro-provincial level characteristics

Characteristics	Unit	Year	Sisaket	Buriram
Per capita income	US$ per year	2017	1,984.8	1,992.5
Road Length	Kilometer	2019	17,414	17,772
Farming households	Number	2017	218,401	191,826
Rice farming households	Number	2017	210,126	182,063
Agricultural land	Thousand hectares	2017	650.8	702.1
Average rice farm size per household	Hectares	2017	2.28	2.41
Jasmine rice growing area	Thousand hectares	2017	433.1	405.4
Jasmine rice production	Thousand tons	2017	908.9	884.1
Jasmine rice consumption	Thousand tons	2017	883.1	1,176.9
Millers	Number	2015	32	26
Aggregate milling capacity	Ton per day	2015	6,614	6,921
Farmer organizations	Number	2018	100	215
Farmer organization members	Number	2018	214,062	216,645
Cooperative rice mill factories	Number	2018	6	5
Aggregate cooperative rice milling capacity	Ton per day	2018	312	183
Cooperative drying factories	Number	2018	2	0
Aggregate cooperative drying capacity	Ton per day	2018	600	0

Source: Authors' compilation using Cooperative Promotion Department (2018a, 2018b), Office of Agricultural Economics(2017), Department of Internal Trade (2017), Department of Agriculture Extension(2017), The Office of Transport and Traffic Policy and Planning (2019), and National Statistical Office of Thailand (2015).

By paying cash on delivery, the SMC purchased approximately 11,000 tons of paddy from both members and non-members. In contrast, farmer organizations in Buriram do not directly compete with private intermediaries in sourcing paddy from farmers. As they feature half the milling capacity and no drying facilities, farmer organizations in Buriram participate in the Jasmine rice value chain by inviting private intermediaries to use their paddy collection centers to buy paddy from farmers.

This difference in practices provides a unique and interesting setting to assess the spillover effect of marketing cooperatives' presence. We can consider some areas within Sisaket as "treated areas" where nonparticipating farmers (farmers who do not sell paddy to farmer organizations) may benefit from the direct competition between marketing cooperatives and private intermediaries. On the other hand, we can use some areas within Buriram as "comparison areas" where nonparticipating farmers forego the benefits from direct competition between marketing cooperatives and private intermediaries.

3.3 The spillover effect of marketing cooperatives and its mechanisms

The presence of marketing cooperatives can generate many kinds of spillover, such as knowledge, reputation, technical efficiency, and pricing strategies (Skevas and Grashuis, 2020). Here, we focus on how the direct competition between marketing cooperatives and private intermediaries in buying paddy could benefit nonparticipating farmers or farmers who choose to sell rice to private intermediaries instead of marketing cooperatives. The idea is that the presence of marketing cooperatives will result in spillover through the change in private intermediaries' pricing behaviors. This change will, in turn, affect the price received by nonparticipating farmers. As an illustration, consider a local rice market with a single miller and a single marketing cooperative. Suppose farmers are uniformly distributed along the distance line, *d,* between these two players at fixed locations, as shown in Figure 3.2.

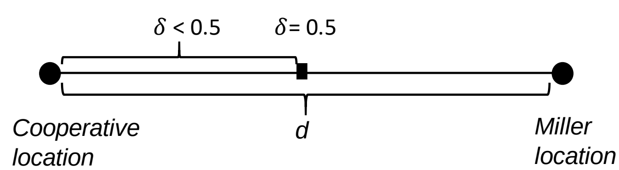

Figure 3.2: Spatial rice market

A farmer faces the choice between selling to the private processor and selling to the marketing cooperative. Let P^{co} and P^{m} denote the per-unit price received from the cooperative and the per-unit price received from the miller, respectively. The per-unit cost incurred by the farmer to transport his/her paddy to the cooperative and the miller is denoted c^{co} and c^{m}, respectively. Similar to farmers' decision whether to sell at the farm gate or to travel to the nearest market in Fafchamps and Hill (2005), the farmer chooses to sell to the cooperative if

$$P^{m} - c^{m} < P^{co} - c^{co} \qquad (3.1)$$

Let δ denote the proportion of the line *d* in which farmers choose to sell to the cooperative. δ has a value between 0 and 1. If $\delta = 0$, no farmers decide to sell to the cooperative. If $\delta = 1$, all farmers sell to the cooperative. For simplicity, we normalize the cost of transportation to 1 per unit distance. We begin by assuming that the cooperative does not practice collective marketing. In this case, we have $\delta = 0$. Now, suppose that the cooperative adopts collective marketing by purchasing an unlimited amount of paddy from both its members and non-members and sell paddy to millers or sell milled rice to retailers (Figure 3.1). First, suppose the cooperative sets the buying price equal to the buying price of the miller, that is, $P^{co} = P^{m}$. We have

$$P^{m} - (1-\delta)d < P^{co} - \delta d \tag{3.2}$$

Solving the above Equation, we have $\delta < 0.5$. In this case, the miller will lose half of its paddy suppliers. Next, we assume that the cooperative sets the price higher than the miller's price. Suppose $P^{co} = P^{m} + b$, where b is the price premium that the cooperative offers on top of the miller's price. Solving Equation 3.2, we have $\delta < 0.5 + 0.5\, b/d$. In this case, without changing the pricing strategy, the miller will lose more than half of its paddy suppliers. This loss is likely to force the miller to change its pricing behaviors in order to retain some paddy suppliers. Let ω denote the level by which the miller increases the buying price. We have

$$\delta < 0.5 + 0.5\,(b-\omega)/d \tag{3.3}$$

Equation 3.3 shows that if the miller wants to retain half of its paddy suppliers, $\delta < 0.5$, it must set price equal to the price offered by the cooperative ($\omega = b$), i.e, $b - \omega = 0$. In contrast, if the miller wants to retain three-quarters of its suppliers, $\delta < 0.25$, it must set price higher than the price offered by the cooperative ($\omega = b + 0.5d$). Therefore, the presence of marketing cooperative is likely to force the miller to raise prices paid to farmers.

Equation 3.3 also indicates that the magnitude of ω or the spillover effect of the presence of the marketing cooperative[42] is depended on the percentage of paddy suppliers that the miller would like to retain (δ), the price premium offered by the cooperative (b), and the geographic proximity between the miller and the cooperative (d). As the variation of these three factors could be driven by several factors, there are many possible mechanisms behind the magnitude of the spillover effect. Given that we focus on the role of marketing cooperative, we discuss only the factors that may affect the price premium level.

At least three factors could affect the price premium level. The first factor is the

[42] As ω will move the market toward competitive equilibrium in imperfect markets, agricultural cooperative theorists have termed it the "pro-competitive effect of marketing cooperatives" or "cooperative yardstick effect" (Liang and Hendrikse, 2016; Sexton, 1990).

cooperative objectives. The cooperative may operate under different objectives, other than maximizing profit. For example, the cooperative may aim to maximize member return or net price. Royer (2014) shows that the price offered by the cooperative is depended on their objectives. The second factor is government subsidy. The government subsidy may lower the cost of doing business of the cooperative compared to the miller's cost. Hence, the cost reduction is likely to affect the level of the price premium. The last factor is the contract choice between the members and the managers of the cooperative. Similar to other organizations, the cooperative faces principal-agent[43] problems (Richards et al., 1998). These problems arise because the agents' (managers) actions, such as work-effort, are not directly observable by the principles (cooperative members). As a result, the agents may not act in the best interests of the principles. Hence, the contract design that will align the manager's personal objective with those of the cooperative will likely affect the price premium offered by the cooperative to members.

3.4 Empirical framework

3.4.1 Identification problem

To explain the difficulty in using location to identify the spillover effect of the presence of marketing cooperatives in a non-experimental setting, we begin by supposing that the true model determining price received by farmers in each location is given by

$$\log(P_{ij}) = \beta_0 + \beta_1 T_i + \beta S_i^o + \beta S_i^u + \beta F_i^o + \beta F_i^u + \beta A_{ij}^o + \beta A_{ij}^u + \varepsilon_{1ij} \qquad (3.4)$$

where P_{ij} is the price received by farmer i in location j; T_i is a farmer's location variable equal to one if the farmer sells rice in areas where there is direct competition between marketing cooperatives and private intermediaries, and zero otherwise; S_i^o is a vector of observable characteristics of rice sale such as the type of buyers; S_i^u is a vector of unobservable characteristics of rice sales such as head rice recovery rate (the proportion of unbroken "head rice" grains per unit of paddy); F_i^o is a vector of observable farmer characteristics such as age; F_i^u is a vector of unobservable farmer characteristics such as ability; A_{ij}^o is a vector of observable local area characteristics such as number of millers; A_{ij}^u is a vector of unobservable local area

[43] The principal-agent model has been extensively used to study the contract choice between landlords and tenants in agrarian economics (Hayami and Otsuka, 1993).

characteristics such as institutional conditions, and ε_{1ij} is an error term assumed to be normally distributed with mean zero.

Since S_i^u, F_i^u, and A_{ij}^u are unobserved, we instead estimate the model

$$\log(P_{ij}) = \beta_0 + \beta_1 T_i + \beta S_i^o + \beta F_i^o + \beta A_{ij}^o + \varepsilon_{2ij} \qquad (3.5)$$

where $\varepsilon_{2ij} = \beta S_i^u + \beta F_i^u + \beta A_{ij}^u + \varepsilon_{1ij}$. This regression is unlikely to yield an unbiased estimate of β_1 because the existence of direct competition between marketing cooperatives and private intermediaries may be partly driven by favorable local area characteristics such as good institutions, and desirable farmer characteristics such as the ability to produce premium quality rice. As a result, part of the observed price differences between farmers in treatment and comparison locations may, either totally or partially, reflect the fundamental difference between them, rather than the presence of direct competition between marketing cooperatives and private intermediaries. Therefore, we have selection bias because we cannot control for all aspects of farmers and locations.

Another difficulty arising from using price as an outcome variable is that we cannot control for important variables such as farmers' marketing decision variables in S_i^o that could significantly affect the price. Farmers' marketing decisions, such as the timing of selling and types of buyers, could substantially affect the price received by farmers. However, these variables are endogenous because they are determined by farmers' price expectations. Local area variables in A_{ij}^o and farmers' characteristics variables in F_i^o might also be endogenous because of their correlation with unobserved features such as farmers' ability. Including these endogenous control variables will lead to a biased estimate of the parameter of interest β_1. To overcome this problem, we could search for instrumental variables for S_i^o, A_{ij}^o, and F_i^o or we could leave S_i^o, A_{ij}^o, and F_i^o out of Equation 3.5. As finding plausible instruments for S_i^o, A_{ij}^o, and F_i^o is difficult, we choose the latter approach. We have

$$\log(P_{ij}) = \beta_0 + \beta_1 T_i + \varepsilon_{3ij} \qquad (3.6)$$

where $\varepsilon_{3ij} = \beta F_i^o + \beta S_i^o + \beta A_{ij}^o + \varepsilon_{2ij}$. Apart from selection bias, this regression suffers from omitted variable bias because S_i^o, A_{ij}^o, and F_i^o in the error term are likely to correlate with T_i. Hence, to be successful in estimating the spillover effect in a non-experimental setting, we must overcome both selection bias and omitted variable bias.

3.4.2 Identification strategy

We address the selection bias and omitted variable bias by using the instrumental variables (IV) approach. This approach is the next best alternative to randomized experiments and is widely used to overcome selection bias and omitted variable problems in estimates of causal relationships (Angrist and Krueger, 2001). The idea behind the IV approach is that we need to find an instrumental variable that is correlated with the variable of interest (relevance assumption) but, at the same time, uncorrelated with the error term (exclusion restriction assumption). If we could find an IV that satisfies these two assumptions, we would obtain a consistent estimator of the coefficient of the variable of interest.

In this paper, we use language spoken at home L_i as IV. Thailand is an ethnically diverse country, hosting approximately 62 ethnic groups with 62 different languages. Central Thai is the most widely spoken language in the country, comprising around 39% of the population. This language is also the sole official language of Thailand. The second most spoken language in the country is Lao Isan, being used by around 28% of the population. The other major languages in the country are Northern-Thai, Southern Thai, and Northern Khmer, being spoken by 10%, 9%, and 3% of the population, respectively (Premsrirat, 2005).

Our IV strategy is justified by the history of village settlement in the Northeast of Thailand (our study region). This history goes back to more than 300 years ago (Keyes, 1967). Specifically, during the formation of the Northeast, a sizeable number of Lao people from Lao, and Khmer people from Cambodia migrated into the area. In particular, most of the villages in treated areas (Sisaket) are Lao Isan[44] speaking villages, whereas most of the villages in comparison areas (Buriram) are Northern Khmer speaking villages. Farmers in these areas are the native-born Thai who speak a language other than Central Thai at home even though they can speak Central Thai fluently. Because language differences originated 300 years ago and have little to do with the present, we expect that, except for language, there should be no systematic difference between Lao Isan and Khmer speakers. To construct the language variable L_i , we included the following question in our survey questionnaire: "Do you speak any language other than Central Thai at

[44] Lao Isan belongs to the Tai language family whereas Northern Khmer belongs to the Austroasiatic language family.

home? If yes, what is this language?". L_i equals one if the farmer speaks Lao Isan at home and zero if he/she speaks other languages at home such as Northern Khmer.

Our IV operates like a randomized promotion process (Gertler et al., 2016). Namely, the language spoken at home (promotion variable) is virtually randomly assigned to farmers, and farmers who speak Lao Isan at home are more likely to sell rice in treated areas. In other words, farmers who receive treatment are partially determined by another variable that is "as if" randomly assigned. Is L_i a good IV for farmers' location T_i? To answer this question, we need to show that L_i is strongly correlated with T_i while at the same time, it is uncorrelated to the price received by farmers or the error term. Because one cannot test the latter, this section discusses its validity in this context.

A) Language and farm management decisions

Language spoken at home may be associated with the price received by farmers through some intermediating cultural variables. The logic is that the language may be associated with certain cultural variables such as social networks, values and beliefs[45], and bargaining power, and those variables may, in turn, influence farmers' farm management decisions and, thus, farm management outcomes. The identifying assumption for our empirical strategy is that the only thing that separates the farmers in our study sites is the language they speak at home and that there are no other cultural aspects that affect their behavior in agricultural markets or the production phase. We discuss two potential areas of concern.

First, language groups may have different social networks and cultures, and those different cultural variables may affect agricultural management. We first investigate whether cultures are linked to farm management in our setting. Several studies have shown that social networks and cultures affect farmers' decisions to adopt new technologies (e.g., Dessart et al., 2019), to manage their farms (e.g., Banerjee et al., 2014; Stifel et al., 2011), and to sale their crops (e.g., Ruhinduka et al., 2020). However, we believe that culture variables no longer affect farm management in our case because agriculture systems in our study sites have undergone a rapid transformation over the last 50 years (Rambo, 2017; Suebpongsang et al., 2020). In terms of Jasmine rice production, farmers in our study areas have abandoned their traditional agricultural practices and have

[45] Social scientists use language spoken at home as a proxy for social networks and cultures (e.g., Bertrand et al., 2000; Ginsburgh and Weber, 2020).

embraced modern agricultural technologies such as chemical fertilizers and mechanization (Soni et al., 2013). In terms of rice marketing, the supermarket revolution (Reardon et al., 2014) and high-quality export standards have driven intermediaries such as millers to conduct their market transactions based on quality standards[46] (Poapongsakorn et al., 2019). As a result, the price received by farmers is determined by paddy quality or grading. These modern marketing practices are likely to reduce the role of personal ties and ethnic on market transaction outcomes.

Moreover, Table 3.5 panel D (section 3.6.1) shows that language spoken at home is unrelated to farmers' marketing behaviors. In addition, the widespread use of a mobile phone, which substantially reduces information transmission costs, is also likely to weaken the cultural mechanism of the diffusion of agricultural knowledge and market information. Besides, recent studies suggest that some cultural traits can be remarkably persistent, whereas some cultural traits tend to disappear more quickly (e.g., Giavazzi et al., 2019). Giuliano and Nunn (2020) show that cultures are likely to disappear if they are not beneficial for the current generation because of the change in technology and economic environments. Therefore, we believe that the language groups' traditional cultures in our study area no longer retain much of the relevance to farm management that might have had in the past.

Next, we investigate whether language groups in our study areas are likely to have similar cultures. If language groups have similar cultures, then our identifying assumption is still valid even if cultural variables affect agricultural management. Apart from language spoken at home, farmers in our study area may have a high degree of cultural similarity because they practice the same religion, Theravada Buddhism (Vail, 2007). These shared cultures are a result of cultural assimilation[47] in our study areas (Keyes, 1967). In fact, social scientists have difficulty classifying cultural groups because individuals differ in skin color, language, the origin of birth, and religion, but it is unclear what dimension should one use. For example, in some countries, language is the key dividing line; in other, it is skin color (Alesina and Ferrara, 2005). Several studies show that religions are associated with individual cultures (e.g., Bryan et al., 2020; Iannaccone, 1998). In an agrarian society, religion provides access to support networks and social insurance against the

[46] This rice value chain upgrading has substantially increased the competitiveness of Thai rice in international markets. As a result, Thailand has become the major rice-exporting country for more than 30 years (Titapiwatanakun, 2012).

[47] For the theoretical analysis of cultural assimilation, see Lazear (1999).

idiosyncratic risk (Ager and Ciccone, 2018). Therefore, although farmers in our study areas speak a different language at home, they may have similar cultures because of religion.

As pointed out by a reviewer, a second legitimate concern is whether it is possible for farmers to keep a language alive for several centuries without anything relevant for agricultural production and markets attached to it. To address this concern, we test the price differences between different languages in the pretreatment period. As we assume that Lao Isan language is associated with the price only through the competition between marketing cooperatives and private intermediaries, we must find no correlation between the language and the price when there is no competition (pretreatment period). However, if we find a correlation, it implies that Lao Isan language has something relevant to agricultural production and markets attached to it. To assess the correlation between the language and the prices, we estimate

$$\log(P_{it}) = \alpha_5 + \alpha_6 L_i + \pi_t year_t + \mu_{it} \tag{3.7}$$

where P_{it} is the price received by farmer *i* in pretreatment year *t*; L_i is language spoken at home (1 = Lao Isan); $year_t$ is year dummy variables; and μ_{it} is an error term. Using unbalanced panel data from the Townsend Thai Project (Townsend, 2016), which gathered household data in our study provinces during the pretreatment period, we find no evidence of the correlation between language spoken at home and the price received by farmers (see section 3.6.1). This finding implies that culture variables are no longer associated with the prices in our setting. It also implies that although farmers maintain their traditional language, they are no longer maintain traditional cultures associated with farm management. This may be the case because a rapid change in agricultural systems during the past 50 years has made it difficult for farmers to maintain traditional cultures associated with farm management. In contrast, language evolves slowly over time because it is difficult to change when language has been widely adopted (Tabellini, 2008). Therefore, it may take more than 50 years for a traditional language to evolve or disappear.

B) Language and farmers' ability

Could the language spoken at home affect farmers' ability? Education economists have investigated the impact of language used in education on human capital formation (e.g., Ramachandran, 2017). Using a language that is different from the language spoken at home as a medium of instruction in school can increase the cost and reduce the efficiency of learning. This method, in turn, will affect knowledge acquisition and student's basic skills such as literacy.

Because the language used in education in Thai schools is different from all languages spoken at home in our study area, if the language has an impact on educational outcomes, this impact will likely cancel each other out. Therefore, the language spoken at home is unlikely to affect farmers' ability in our setting.

C) Language and the development of farmers' organizations

Despite facing identical national institutions, the development of farmers' organizations in two areas end up with different outcomes. The critical assumption underlying our analysis is that these differences are unrelated to cultural factors associated with language spoken at home. A reviewer points out that cultures[48] associated with language groups may affect the development of farmers' organizations. In particular, given that the vast majority of farmers speak Lao Isan in Thailand, it may be easier for farmers' organizations whose members speak Lao Isan to form and grow. Namely, farmers who speak the same language may have more trust in each other, and trust may enable the member of farmers' organizations to act together more effectively to pursue shared objectives. This, in turn, may increase the number of farmers participating in farmers' organizations. If trust due to language is associated with cooperative size (as measured by the number of members) and the size is, in turn, associated with the investment in post-harvesting technologies, using language as the instrument is problematic. We consider this possibility unlikely in our setting for three reasons.

First, not all Lao Isan speaking provinces invest in modern drying technology. If Lao Isan language is associated with cooperative size and the size is associated with the investment in drying technology, then all Lao Isan speaking provinces where Jasmine rice is grown will invest in the technology. However, according to data from Ministry of Industry (2020), agricultural cooperatives in Mahasarakham, Yasothon, and Amnatcharoen provinces do not invest in drying technology even though most of the farmers in these provinces speak Lao-Isan at home and the Jasmine rice production in these provinces accounted for 10% of total Jasmine rice production (Office of Agricultural Economics., 2019).

Second, there may be no correlation between language and cooperative size. This may be the case because although farmers speak a different language, they share the same religious beliefs,

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[48] Political economy literature has shown that cultural traits such as trust matter for various economic outcomes such as the quality of institutions (Alesina and Giuliano, 2015).

which may increase trust between them. Moreover, it may be that the level of trust is not associated with language spoken at home. Study in the U.S. shows that individual culture, traditions, and religions do not significantly affect trust. Trust seems to be associated with personal experiences, the perception of being part of the discriminated group, and racial and income heterogeneity (Alesina and La Ferrara, 2002).

Lastly, even if the language is correlated with cooperative size, we find no correlation between cooperative size and milling capacity in our setting. To test the association between cooperative size and milling capacity, we regress the cooperative rice milling capacity (*millca*) in Thailand on cooperative size (*size*):

$$Millca_n = \alpha_8 + \alpha_9 Size_n + \mu_n \tag{3.8}$$

where *n* indicates agricultural cooperatives and μ_n is an error term. The results in section 3.6.1 show no significant correlation between cooperative size and milling capacity. This result may arise because 83% of the investment in post-harvest technologies used outside funding from the special loans or assistance programs. The majority of these programs responded to some economic shocks. For example, 49% of the investment used funding initiated to mitigate the 1997 Asian financial crisis that significantly devastated the Thai economy (Abonyi, 2005). Hence, the investment may depend on the loan programs' conditions and other factors, rather than cooperative size. Therefore, we believe that cultures associated with language groups are unlikely to correlate with farmers' organizations' development in the two areas.

D) Province fixed effect and price

Our analysis assumes that there is no price difference between Buriram and Sisaket in the pretreatment period. This assumption is necessary to validate our exclusion restriction assumption because our IV (the language spoken at home) is correlated with the province fixed effect[49] as all of our treatment samples are located within one province.

[49] the province time-invariant characteristics such as location

To test the association between the province fixed effect and the price, we estimate

$$\log(P_{it}) = \pi_3 + \pi_4 S_i + \pi_t year_t + \mu_{it} \tag{3.9}$$

where S_i is dummy variable (province fixed effect) equal to one if farmers i are in Sisaket and zero if they are in Buriram; and μ_{it} is an error term. Using the data from The Townsend Thai Project, we find no significant association between province fixed effect and the price (see section 3.6.1). In other words, there is no significant price difference between the two areas during the pretreatment period. Therefore, the province fixed effect in the error term does not lead to the violation of the exclusion restriction assumption.

Given that language spoken at home is a valid IV, we estimate

$$\log(P_{ij}) = \beta_0 + \beta_1 \hat{T}_i + \varepsilon_{4ij} \tag{3.10}$$

where $\hat{T}_i$ is the predicted value of T_i obtained from the first-stage regression of farmers' location on language spoken at home and all the control variable in Equation 3.10, which is such that

$$T_i = \alpha_0 + \alpha_1 L_i + \varepsilon_{5ij} \tag{3.11}$$

The interpretation of β_1 in this case is an approximate effect of treatment on the subset of farmers who would not sell rice in treated areas if they were not born into Lao Isan speaking families (Imbens and Angrist, 1994). That is, the coefficient β_1 is the local average treatment effect (LATE) of the presence of marketing cooperatives on the price received by farmers.

3.5 Data and descriptive statistics

Figure 3.3 depicts our study areas. To support the sampling design, we constructed a Geographic Information Systems (GIS) database for Sisaket and Buriram that include road networks, agricultural cooperatives' locations, rice miller locations, and village locations. Road networks were obtained from the Ministry of Transport (2016). Agricultural cooperative locations and rice millers' locations were obtained from the Ministry of Agriculture and Cooperative (2019). Village locations were obtained from the Department of Provincial Administration (2014).

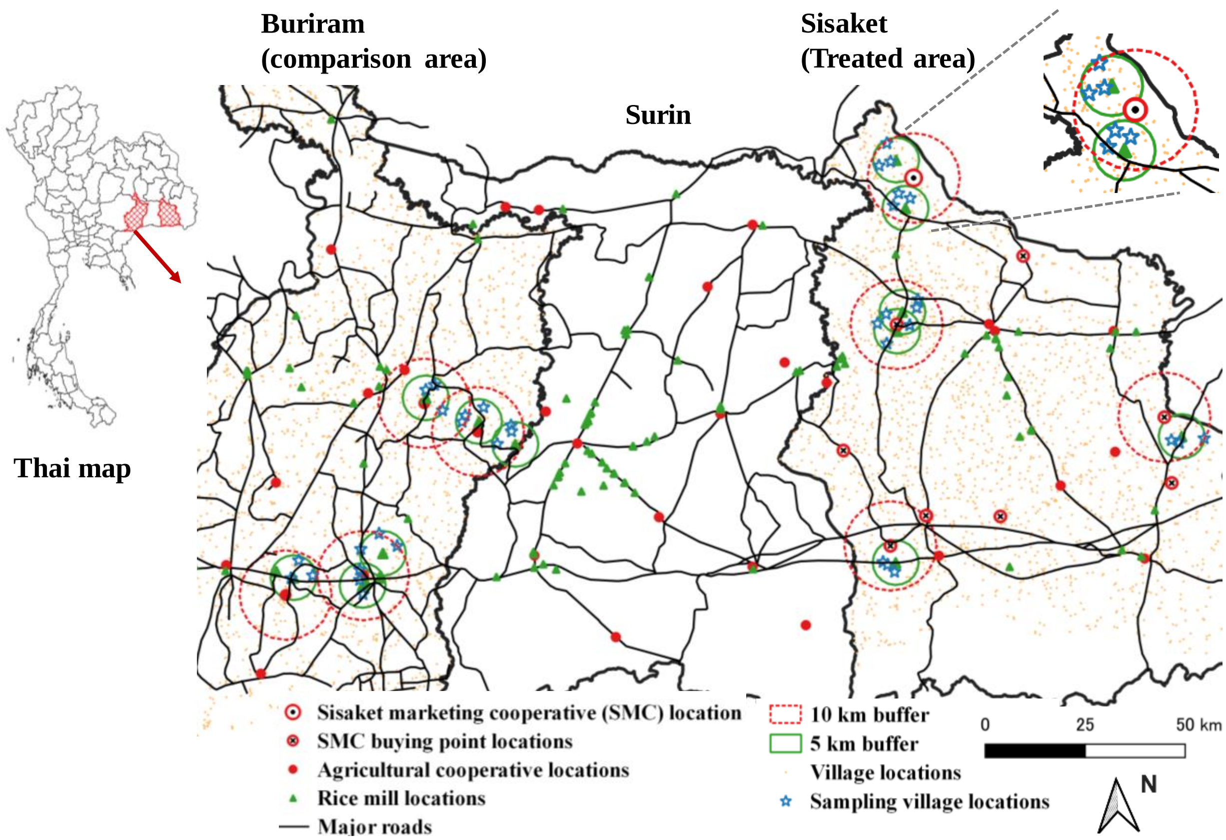

Figure 3.3: Our study areas

We used a multistage sampling procedure to randomly select 180 farm households from 18 villages in treated areas and 180 farm households from 18 villages in comparison areas. First, we purposively selected the Sisaket marketing cooperative (SMC) and three agricultural cooperatives that cooperated with the SMC to compete with private intermediaries in buying rice from farmers. On the other hand, in Buriram, we purposively selected four agricultural cooperatives that do not compete with private intermediaries in buying rice from farmers. Second, as we are interested in private intermediaries that compete with the marketing cooperatives, we used GIS to generate a list of private intermediaries (only rice mills) that are located within 10 kilometers of agricultural cooperatives. Our list counted 17 private intermediaries. After that, we selected one or two private intermediaries per agricultural cooperative. In total, we selected six private intermediaries in Sisaket and six private intermediaries in Buriram. Third, because the spillover effect transmits to nonparticipating farmers through private intermediaries, we used GIS to generate the list of villages that are located within five kilometers of selected private intermediaries. Since we want to obtain samples of farmers who sell rice to private intermediaries, we dropped villages that are closer to the cooperative than private intermediaries. In Buriram, we also dropped 12 Lao Isan speaking villages in order to make sure that the language spoken at home (Lao Isan) is only correlated with samples within treated areas. In total, we retained 157 villages in Sisaket and 131 villages in Buriram. Fourth, we randomly selected three villages per private intermediary. This process resulted in a total of 36 villages to be surveyed. Lastly, we randomly selected ten households from a complete list of rice farming households in each village, which we obtained from the Community Development Department (2017). When a household could not be found, we interviewed the next one on the list. Ultimately, we obtained a sample size of 360 households from 36 villages. We collected data in the period June–July 2019. We interviewed farmers face-to-face and gathered data on the characteristics of farmers, areas, and rice sales[50] related to the 2018/19 marketing year (see appendix Q for questionnaire).

To support the validity of our IV, we use data from two sources. First, we use data from the Townsend Thai Monthly Survey[51], a survey that gathered a wide range of household data from 1998 to 2014 in four provinces in Thailand. The components used in our study only include detailed data on households' crop sales. We restrict our sample to households that lived in Sisaket and Buriram and sold Jasmine rice to intermediaries (not institution or government agency). As a result, we have 848 samples (430 from Sisaket and 418 from Buriram), running from 1999 to 2004[52]. Second, we use cooperative rice milling capacity and cooperative size data from Cooperative Promotion Department (2020a, 2020b). Table 3.2 reports the descriptive statistics.

[50] One limitation of our study is that we did not collect rejection rates and payment modes even though, as pointed out by a reviewer, these variables may differ between the two areas.

[51] For more detailed description and information regarding the data set, please refer to the Townsend Thai Project web site at http://townsend-thai.mit.edu/data/monthly-surveys.shtml.

[52] The sample is dropped after 2004 because no sample in Buriram sold Jasmine rice to intermediaries between 2005 to 2014.

Table 3.2: Summary statistics

Variables	Unit	Selling locations			
		Treated areas		Comparison areas	
		Mean	Std. dev.	Mean	Std. dev.
Paddy rice sale characteristics					
Paddy price received	Baht/kilogram	13.78	1.683	12.53	1.957
Selling quantity	ton	2.574	2.635	3.241	3.882
Selling wet paddy	1 = wet paddy	0.583	0.494	0.622	0.486
Selling to miller	1 = miller	0.522	0.501	0.606	0.490
Selling the best quality [a]	1 = best quality	0.411	0.493	0.583	0.494
Selling pure variety [b]	1 = pure variety	0.789	0.409	0.844	0.363
Selling in January	1 = January	0.038	0.194	0.027	0.165
Selling in February	1 = February	0.022	0.148	0.016	0.128
Selling in March	1 = March	0.050	0.219	0.027	0.165
Selling in April	1 = April	0.022	0.148	0.016	0.128
Selling in May	1 = May	0.111	0.315	0.044	0.207
Selling in June	1 = June	0.044	0.207	0.100	0.301
Selling in July	1 = July	0	0	0.033	0.180
Selling in October	1 = October	0.161	0.369	0.150	0.358
Selling in November	1 = November	0.478	0.501	0.572	0.496
Selling in December	1 = December	0.072	0.260	0.011	0.105
Farmer characteristics					
Age	Years	57.73	11.26	56.24	10.19
Male	1 = male	0.461	0.500	0.517	0.501
Education	Years	5.972	3.172	5.939	3.425
Household size	Number	3.961	2.053	3.967	1.704
Farm size	Hectares	2.599	2.301	4.244	3.432
Born	1 = inside villages	0.694	0.461	0.688	0.464
Off-farm work	1 = yes	0.422	0.495	0.461	0.499
Lao Isan	1 = Lao Isan	0.928	0.260	0	0
Local area characteristics					
Number of millers	Number	2	1.418	1.667	1.109
Milling capacity	100 tons/day	4.783	1.862	4.533	4.601
Observations	Number of farmers	180		180	
Data used to support the validity of IV					
Townsend Thai Data					
Paddy price received[c]	Baht/kilogram	6.50	1.333	6.46	1.22
Lao Isan[d]	1 = Lao Isan	1	0	0.212	0.409
Observations	Number of sales transactions	430		418	
Agricultural cooperative data					
Milling capacity	Ton/day	36.25		31.59	
Size	Number of member (thousand)	8.960		26.42	
Observation	Number of cooperatives	147			

Notes: [a] In our survey questionnaire, we included the question, "When you sell your paddy, do you receive the maximum announced price?" If the answer is yes, it implied that the paddy has the highest quality. [b] No heterogeneous mix of varieties, [c] we construct this variable by dividing the transaction's cash value by the quantity of paddy sold. [d] The Townsend Thai Data does not collect the language variable, we construct this variable by using the village-level language data. If most of the villagers in villages speak Lao Isan at home, we assign Lao Isan language to all households surveyed in this village.

3.6 Results and robustness checks

3.6.1 Instrumental variable's validity

Before presenting and discussing estimation results, in this section, we further illustrate the IV's validity. First, to check whether the language spoken at home is virtually randomly assigned, we compare the demographic characteristics of households featuring different languages spoken at home. Table 3.3 suggests that, except farm size, none of the demographic characteristics is significantly different from zero at the one percent level. These results make intuitive sense as one cannot choose the family in which one is born.

Table 3.3: Demographic characteristics of farmers by language spoken at home

	Language spoken at home		
	Lao Isan	Non-Lao Isan	Difference
	(1)	(2)	(3)
Age	57.76	56.32	1.444
	[0.88]	[0.73]	[1.135]
Education	5.96	5.95	0.005
	[0.24]	[0.25]	[0.349]
Male	0.44	0.53	–0.085
	[0.04]	[0.04]	[0.053]
Born (inside village = 1)	0.69	0.69	0.005
	[0.04]	[0.03]	[0.049]
Household size	3.97	3.96	0.012
	[0.16]	[0.13]	[0.199]
Off-farm work (1 = yes)	0.42	0.46	–0.042
	[0.04]	[0.04]	[0.053]
Farm size (hectares)	2.61	4.12	–1.511***
	[0.18]	[0.24]	[0.311]
Observations	167	193	360

Note: The figures in brackets below the estimates are the standard errors. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.

Next, to illustrate the relationship between the language spoken at home and the price received by farmers, Figure 3.4 presents the Cumulative Distribution Functions (CDFs) of the price received by farmers, differentiated according to the language spoken at home. The vertical axis of the CDFs shows the cumulative proportion of all farmers with the price received less than or equal to the corresponding price on the horizontal axis. The key finding here is that the Lao Isan CDF curve lies entirely below the Non-Lao Isan one. In other words, for all prices received, the share of farmers that receive low prices is relatively larger among Non-Lao Isan speaking than among Lao speaking farmers. For example, 64% of Non-Lao Isan speaking farmers receive a price less than the average price of 13.2 baht per kilogram of paddy (red line), whereas only 38% of Lao Isan speaking farmers receive a price less than that price. Because language spoken at home is unlikely to affect the price received directly, once farm size is controlled for, it must affect the price received through treatment status.

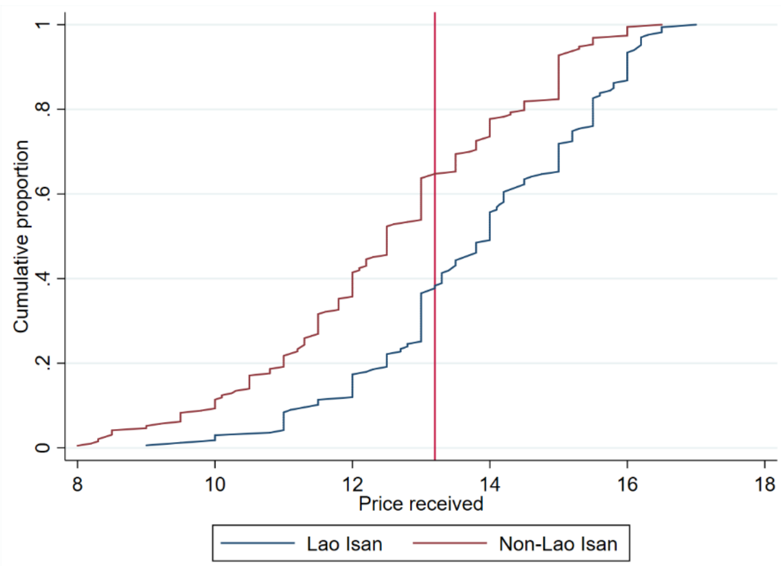

Figure 3.4: Cumulative distribution functions of the price received by farmers, differentiated according to the language spoken at home

In Table 3.4, we examine the relationship between the language spoken at home and rice selling locations or treatment status. Different columns in Table 3.4 exhibit the estimations from several specifications of first-stage IV regression (Equation 3.11). As shown in columns (1) – (4), language spoken at home is highly correlated with rice selling locations and statistically significant at the 1% level. The coefficients suggest that at least 93% of farmers who sell rice in the treated area speak Lao Isan at home. Hence, our results confirm that the language spoken at home is highly correlated with the treatment variable.

Table 3.4: First-stage regressions and instrument relevance

	Dependent variable: Selling in treated areas			
	(1)	(2)	(3)	(4)
Independent variables				
Lao Isan	0.933***	0.935***	0.935***	0.923***
	[0.060]	[0.059]	[0.060]	[0.069]
Male		0.024	0.024	0.026
		[0.017]	[0.017]	[0.016]
Education			0.001	0.002
			[0.003]	[0.003]
Age				–0.001
				[0.001]
Household size				0.000
				[0.001]
R-squared	0.865	0.866	0.866	0.868
Observations	360	360	360	360

Note: The figures in brackets below the estimates are the standard errors, clustered by selected cooperatives. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

In Table 3.5, we perform various tests to support the validity of the exclusion restriction assumption. In panels A, B, and C we estimate Equation 3.7, 3.8, and 3.9, respectively. In panel A, we find that Lao Isan language is unrelated to the price received by farmers during the pretreatment period. Panel B indicates that there is no association between milling capacity and cooperative size. In panel C, we find no significant correlation between the prices and the province fixed effect during the pretreatment period. These pieces of evidence validate that the IV exclusion restriction is fulfilled.

As we have some observable variables contained in ε_{3ij} (Equation 3.6), we can also check whether our IV and the observable variables in the error term are uncorrelated. In panel D, we partly test the exclusion restriction assumption. Our results confirm that language spoken at home is unrelated to farmers' marketing decisions and local area characteristics; however, it is correlated with farm size. The significance of farm size is a limitation of language as an IV as farm size is expected to affect the price as well—larger farm size is expected to increase bargaining power. Nevertheless, in our case, farm size is not correlated with the price (see Table 3.6). This may be the case because farm sizes in our study area are not large enough to increase farmers' bargaining power significantly. In contrast, if farm size is correlated with the price, which in turn will cause our IV to affect the price indirectly, this indirect effect could be eliminated by including the farm size variable in Equation 3.10. Therefore, we maintain that the exclusion restriction assumption is still valid. Nevertheless, we will relax this assumption later in our robustness check (see section 3.6.3.2).

Table 3.5: Testing to support the validity of the exclusion restriction assumption

Panel A: Dependent variable is paddy price received	
Independent variables:	OLS
Lao Isan (1 = Lao Isan)	-0.021
	[0.019]
Control for year	Yes
R-squared	0.603
Observations	848

Panel B: Dependent variable is milling capacity	
Independent variables:	OLS
The size of agricultural cooperatives	0.043
	[0.074]
R-squared	0.001
Observations	147

Panel C: Dependent variable is paddy price received	
Independent variables:	OLS
Sisaket (1 = Sisaket)	-0.022
	[0.016]
Control for year	Yes
R-squared	0.604
Observations	848

Panel D: Dependent variable is Lao Isan	
Independent variables:	OLS
Farmers' marketing decisions	
Selling wet paddy	–0.015
	[0.094]
Selling to miller	0.012
	[0.121]
Selling months	–0.025
	[0.014]
Local area characteristics	
Number of millers	0.109
	[0.143]
Milling capacity	–0.000
	[0.000]
Farmer characteristics	
Farm size	–0.007***
	[0.002]
Household size	0.009
	[0.019]
Age	0.002
	[0.003]
Male	–0.064
	[0.056]
Education	0.010
	[0.014]
R-squared	0.144
Observations	360

Note: The figures in brackets below the estimates are the standard errors, clustered by villages in panel A and C and by cooperatives in panel D. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

3.6.2 Results

We estimate Equation 3.5, 3.6, 3.10, and present the results in Table 3.6 in columns (1), (2), (3), respectively. Before discussing the estimation result for the conclusion of this study in column (3), we begin with the simple analysis of the spillover effect of the presence of marketing cooperatives, i.e., an increase in rice price due to direct competition between marketing cooperatives and private intermediaries. Column (1) in Table 3.6 reports the results of an OLS regression to analyze the association between farmers' locations and the price received. Controlling for other variables, farmers who sell rice to private intermediaries in the area where there is direct competition between marketing cooperatives and private intermediaries receive an 11.8% higher price than those who sell rice in other areas. The remaining results in column 1 also have a reasonable association. For example, farmers who sell wet paddy receive a 14% price discount relative to those who sell dry paddy. Column (2) drops the characteristics of rice sale, farmer, and local area variables. The coefficient on selling locations remains highly statistically significant, but its magnitude drops by approximately two percentage points. As discussed in section 3.4.1, the OLS regressions in columns (1) and (2) are unlikely to have a causal interpretation.

The regression presented in column (3) attempts to make a causal link between marketing cooperatives' presence and the price received. We use the same specification as in column (2), but we apply the two-stage least square (2SLS) procedure to estimate the spillover effect of marketing cooperatives using the language spoken at home as an IV. In the last row, we report the F-statistic for the first-stage regression for the treatment variable. The instrument appears sufficiently strong to avoid bias caused by weak instruments.

Table 3.6: OLS and 2SLS estimates of the spillover effect of marketing cooperatives

	Dependent variable: Log (price received)		
Estimation method	OLS	OLS	2SLS
	(1)	(2)	(3)
Independent variables			
Selling in treated areas	0.118***	0.099**	0.109***
	[0.017]	[0.038]	[0.032]
Selling quantity	0.003**		
	[0.001]		
Selling wet paddy	–0.135***		
	[0.033]		
Selling to miller	0.008		
	[0.011]		
Selling the best quality	0.079***		
	[0.013]		
Selling pure variety	0.067*		
	[0.028]		
Selling in January	0.032		
	[0.033]		
Selling in February	–0.055		
	[0.037]		
Selling in March	–0.036		
	[0.021]		
Selling in April	–0.004		
	[0.023]		
Selling in May	–0.023		
	[0.016]		
Selling in June	–0.022		
	[0.019]		
Selling in October	–0.136***		
	[0.033]		
Selling in November	–0.112**		
	[0.042]		
Selling in December	–0.130**		
	[0.045]		
Age	–0.001		
	[0.001]		
Male	–0.001		
	[0.007]		

Table 3.6: (continued)

	Dependent variable: Log (price received)		
Estimation method	OLS	OLS	2SLS
	(1)	(2)	(3)
Independent variables			
Education	–0.000		
	[0.002]		
Farm size	–0.000		
	[0.000]		
Household Size	0.003		
	[0.002]		
Number of millers	–0.015***		
	[0.004]		
Milling capacity	0.007*		
	[0.004]		
Observations	360	360	360
R–squared	0.625	0.103	0.102
First stage F–statistic			239.0

Note: The figures in brackets below the estimates are the standard errors, clustered by cooperatives. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

The IV estimates strongly confirm our hypothesis that nonparticipating farmers or farmers who sell rice to private intermediaries in the areas where there is direct competition between marketing cooperatives and private intermediaries (treated areas) are likely to receive a higher price than those who sell rice in other areas (comparison areas). The estimated coefficient for treatment status is statistically significant and indicates that nonparticipating farmers in treated areas receive an 10.9% higher price from private intermediaries than those in comparison areas. Interestingly, the IV estimate of the spillover effect does not differ much from the OLS estimate, suggesting that the OLS estimate features little selection and omitted variable bias. On the other hand, one could also interpret this as showing that our IV may be correlated with the error term (see section 3.6.3.2).

Investigating whether the spillover effect varies as a function of farmers' characteristics such as gender and cooperatives' characteristics such as size is an important and interesting issue. However, measuring the spillover effect's heterogeneity can create a fatal bias because we could not overcome the problem of "bad controls." Namely, to measure the spillover effect's heterogeneity, we have to include farmers' characteristic variables and cooperatives' characteristic variables and the interaction term between these variables and selling in treated area variable in Equation 3.10. Nevertheless, as discussed in section 3.4.1, these variables are endogenous. For example, farmers' characteristic variables such as age and education are likely to correlate with farmers' marketing decision variables in the error term. Including these endogenous variables as control variables can yield the serious bias results of the spillover effect. This is what Angrist and Pischke (2014, 2008) call "bad controls" problems. To overcome bad control problems in our case, we must search for instrumental variables for each endogenous control variable (male, education, farm size, age, household size, cooperatives' size, the percentage of the female member in cooperatives). Given that finding a valid instrument variable is very difficult and our paper's primary goal is to establish the causal link between the presence of marketing cooperatives and price received by farmers, i.e., to estimate the average treatment effect, we leave the issue of spillover effect heterogeneity for future research.

3.6.3 Robustness checks

In this section, we demonstrate the robustness of our results by (i) controlling for the observable difference between treated and control areas or observable heterogeneity, while (ii) allowing for correlation between the instrument and unobserved heterogeneity, i.e., we relax the exclusion restriction assumption.

3.6.3.2 Controlling for observable heterogeneity

One may worry that our instrument is picking up nonmarketing cooperative-related differences in prices received across areas with the different languages spoken at home, which in turn will result in biased estimates of the spillover effect. To address this concern, we first report the comparison of variables between treatment and comparison areas. Table 3.7 confirms that farmers in treatment and comparison areas do significantly differ at the 10% level (but not at the 5% level) in quantity sold and choice of selling time. The number of millers also significantly differs at the 5% level while paddy quality and farm size significantly differ at the 1% level. Therefore, we examine whether our results are robust to controlling for those variables, plus other interesting variables. However, as those variables are potentially endogenous, we cannot control them by including them in the estimated equation. For this reason, we split the sample based on those variables into seven groups and estimated the treatment effect for each sub-sample (Table 3.8).

Table 3.7: Comparison of variables between treated and comparison areas

	Selling locations		
	Treated areas	Comparison areas	Difference
	(1)	(2)	(3)
Selling quantity	2,574.29	3,241.41	–667.122*
	[196.43]	[289.38]	[349.749]
Selling wet paddy	0.58	0.62	–0.039
	[0.04]	[0.04]	[0.052]
Selling to millers	0.52	0.61	–0.083
	[0.04]	[0.04]	[0.052]
Selling the best quality	0.41	0.58	–0.172***
	[0.04]	[0.04]	[0.052]
Selling pure variety	0.79	0.84	–0.056
	[0.03]	[0.03]	[0.041]
Selling in October	0.16	0.15	0.011
	[0.03]	[0.03]	[0.038]
Selling in November	0.48	0.57	–0.094*
	[0.04]	[0.04]	[0.053]
Age	57.73	56.24	1.483
	[0.84]	[0.76]	[1.132]
Male	0.46	0.52	–0.056
	[0.04]	[0.04]	[0.053]
Education	5.97	5.94	0.033
	[0.24]	[0.26]	[0.348]
Farm size	2.6	4.24	–1.645***
	[0.17]	[0.26]	[0.308]
Number of millers	2	1.67	0.333**
	[0.11]	[0.08]	[0.134]
Milling capacity	478.33	453.33	25
	[13.88]	[34.29]	[36.994]
Observations	180	180	360

Note: The figures in brackets below the estimates are the standard errors. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

In Table 3.8, we estimate the treatment effect for each sub-sample by using the same empirical specification as in Table 3.6, i.e., columns (1), (2), and (3) in Table 3.8 are the same as columns (1), (2), (3) in Table 3.6. However, unlike in Table 3.6, we only report the estimated coefficient of the "Selling in treated areas" variable for comparison purposes. The estimated coefficients of other variables are reported in Appendix B. Column (1) and (2) present OLS estimates of the spillover effect and column (3) presents IV estimates. For example, by restricting the sample to only farmers who sell the best paddy quality, the IV estimate of the spillover effect is approximately 11.8%, compared with an OLS estimate of about 11.2% in column (2) and 14.6% in column (1). In column (3), the IV estimates of the spillover effect (ranging from 7.1% to 16.1%) in each restricted sample are statistically significant and within 5 percentage points of the corresponding estimates from the full sample. Therefore, our main finding is robust to controlling for observable heterogeneity.

Table 3.8: The spillover effect of marketing cooperatives: robustness check

		Dependent variable: Log (price received)				
		Coefficient on selling in treated areas				
	Observations	OLS (1)	OLS (2)	2SLS (3)	First stage F-statistic (4)	IIV (5)
Full sample	360	0.118***	0.099**	0.109***	239.0	[0.109, ∞)
		[0.017]	[0.038]	[0.032]		
Restricted sample						
Selling the best quality sample	179	0.146***	0.112***	0.118***	171.9	[0.118, ∞)
		[0.016]	[0.024]	[0.023]		
Selling to miller sample	203	0.110***	0.068	0.071**	407.2	[0.071, ∞)
		[0.018]	[0.037]	[0.033]		
Selling to trader sample	116	0.136***	0.096*	0.119***	120.2	[0.119, ∞)
		[0.025]	[0.048]	[0.042]		
Selling wet paddy sample	217	0.119***	0.110***	0.112***	110.4	[0.112, ∞)
		[0.012]	[0.024]	[0.021]		
Selling at November sample	190	0.133***	0.127***	0.124***	112.1	[0.127, ∞)
		[0.030]	[0.036]	[0.033]		
Single miller in the area sample	240	0.159**	0.088	0.099**	96.3	[0.099, ∞)
		[0.047]	[0.047]	[0.039]		
Selling the best quality wet paddy to miller at November sample	59	0.156***	0.156***	0.161***	72.1	n.a
		[0.020]	[0.035]	[0.033]		

Note: The quantities in blankets below the estimates are the standard errors, clustered by cooperatives. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

3.6.3.2 Relaxing the exclusion restriction assumption

The correlation between our IV and farm size raises a concern about the validity of our IV exclusion restriction assumption. Namely, even though farm size is not correlated with price, our IV may be associated with other unobservable variables that could affect price. To address this concern, we explore a recent methodology for inference with instruments that fail the exclusion restriction assumption. Nevo and Rosen (2012) establish that it is possible to consistently estimate economically meaningful upper and lower bounds on the true parameter value by replacing the exclusion restriction assumption with an assumption about the sign of the correlation. That is, the correlation between the instrument and the unobserved error term must have the same direction as the correlation between the endogenous regressor and the error term (Nevo and Rosen, 2012, assumption 3). As we have some observable variables contained in error terms such as farm size, we can check whether the endogenous variable and the IV satisfy Nevo and Rosen's imperfect instrumental variables (IIV) assumption. Regressing our IV on farm size, we obtain a negative coefficient with t-value of –4.8 while regressing treatment variable on farm size, we also get a negative coefficient with t-value of –5.3. Therefore, both the variables satisfy the IIV assumption. Table 3.8, column (5) shows our results from using the procedure suggested by Nevo and Rosen (2012). By employing the IIV estimation method, we can generate one-side lower bounds for the true coefficients of selling in the treated area variable. Namely, if our instrument violates the exclusion restriction assumption, our IIV estimates provide a lower bound for the spillover effect. For example, in the full sample, the true value of the spillover effect is greater than or equal to 10.9%. Therefore, these results reassure that the spillover effect of marketing cooperatives is positive and statistically significant, even allowing for plausible amounts of correlation between our IV and the error term.

3.7 Implications for policy and evaluation

Our results carry four crucial implications for policymakers and evaluators. First, we provide empirical evidence to support the view that evaluating the inclusiveness of marketing cooperatives toward poor farmers should not be limited to sampling and analyzing marketing cooperative members only (Bernard and Spielman, 2009). Information on whether cooperatives are inclusive of poor farmers is essential because of the high relevance of agricultural cooperatives in policy debates on rural development, food security, and agricultural sustainability. Prior theoretical and empirical literature evaluated the inclusiveness of cooperatives based on a sample of cooperative members only. Most of these studies indicate that poor farmers do not tend to participate in agricultural cooperatives (Bijman and Wijers, 2019). However, our study empirically shows that poor farmers can indirectly benefit from the spillover effect of marketing cooperatives regardless whether the latter are inclusive or not. Therefore, evaluating the inclusiveness of marketing cooperatives should include a sample and analysis of nonparticipating farmers in the area where the marketing cooperatives operate.

Second, prior studies that do not control for the spillover effect may underestimate the effects of marketing cooperatives on societal welfare. For example, suppose a marketing cooperative increases the price received by participating farmers by ten percentage points. Simultaneously, the marketing cooperative's presence also increases the price received by nonparticipating farmers by eight percentage points. Suppose we do not control for the spillover effect. In that case, we will observe only a two-percentage-point increase in the price received by participating farmers even though the actual effect is ten percentage points. Therefore, the failure to recognize the spillover effect of marketing cooperatives will result in a double underestimation of the impact of marketing cooperatives on societal welfare. That is, not only will its effect on participating farmers be underestimated, but its effect on nonparticipating farmers will also remain unmeasured.

Third, the spillover effect needs to be incorporated in the future evaluation of a marketing cooperative's performance. Our study shows that the spillover effect is a critical dimension of the economic performance of the marketing cooperative. Therefore, failure to consider the spillover effect may lead to erroneous policy conclusions and recommendations.

Lastly, the free rider problem is a major challenge of grain marketing cooperatives. The free rider problem refers to the situation where a non-member captures benefits associated with the provision of public goods by the cooperative but avoids becoming a member. Although Cook (1995) suggested that the free rider problem may be a minor problem for marketing cooperatives, the spillover effect we identified actually does generate a free rider problem as it reduces farmers' incentives to become a cooperative member. As a result, the costs associated with the marketing cooperative activities will be incurred by members alone, and not by all beneficiaries. Therefore, policies aiming at enhancing the role of marketing cooperatives in premium rice value chains should be aware of and address the free-rider problem to ensure that societal welfare is maximized.

3.8 Conclusion

Despite the widespread belief that marketing cooperatives' benefits may extend beyond participating farmers, little progress has been made in estimating the spillover effect of marketing cooperatives. We collected household-level data from 360 randomly selected rice farmers in Thailand in 2019 to investigate the effect of the presence of marketing cooperatives on the price received by nonparticipating farmers. We identified an exogenous variation in the language spoken at home and its correlation with selling locations or treatment status. Using language spoken at home as an instrumental variable, we obtained empirical results that are robust across various specifications and consistent with theoretical predictions. To the best of our knowledge, this study is the first attempt to empirically unveil the existence and magnitude of the spillover effect of marketing cooperatives in agricultural value chains.

Our analysis suggests that farmers are better off selling their rice if they sell it in the area where there is direct competition between marketing cooperatives and private intermediaries (treated areas). Namely, farmers in treated areas receive a 10.9% price premium from private intermediaries relative to those who sell rice in other areas. This result provides support for the view that the presence of marketing cooperatives can significantly force private intermediaries to competitively raise prices paid to farmers.

Our empirical findings have crucial implications for food policy debates regarding the role of marketing cooperatives in agricultural development. First, evaluating the inclusiveness of marketing cooperatives toward poor farmers should not be limited to sampling and analyzing participating farmers only, because poor farmers can benefit from the spillover effect of marketing cooperatives, whether the latter are inclusive or not. Second, prior studies that do not control for the spillover effect of marketing cooperatives may underestimate the effects of marketing cooperatives on participating farmers as well. Third, the spillover effect needs to be incorporated in the future evaluation of the marketing cooperative's performance. Failure to consider the spillover effect could lead to substantial underestimation of the impact of marketing cooperatives on societal welfare. Finally, the free rider problem is a significant challenge for marketing cooperatives that needs to be addressed.

This study has some limitations. First, although we found language to be a good instrumental variable in the context of our study of Thai rice farmers, it may be imperfect. If this is the case, our imperfect instrumental variable estimate provides a lower bound for the spillover effect. Secondly, while the investigation focuses on the Thai Jasmine rice value chain, it is not clear whether similar results would hold in other settings. Future research using data from other crops and countries is needed to enlarge our knowledge about the spillover effect of marketing cooperatives in agricultural value chains.

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Appendix

A. Cooperative investments in post-harvest technologies in the two areas

Table A: Detail of cooperative investments in post-harvest technologies in Buriram and Sisaket

Name	Types of facility	Capacity (ton/day)	Year of investment	Sources of funding*	Member
Sisaket					
Muang sisaket	Milling	80	1983	CPD	7,741
Wanghin	Milling	12	1994	PDB	2,122
Kantharaluck	Milling	60	1999	CPD	5,050
	Drying	300	2015	FTA fund, BAAC	
Sikanthararom	Milling	40	2001	ADB	6,387
Sisaket marketing-cooperative	Milling	80	2006	CPD	136,765
	Drying	300	2016	Self-funding	
Phusing	Milling	40	2011	CPD	1,487
Buriram					
Krasang	Milling	24	2000	Japan's ODA	3,988
Buriram cooperative federations	Milling	100	2000	CDF	-
Buriram's farmers	Milling	1	2001	LG	503
Nang Rong	Milling	40	2002	ADB	4,678
Buriram marketing cooperative	Milling	24	2018	CPD	109,399

CPD = Cooperative Promotion Department, PDB = Provincial Development Budget, ADB = Asia Development Bank through agricultural sector program loan, ODA = Official Development Assistance, CDF = Cooperative Development Fund, LG = Local Government, FTA = Free Trade Agreement

Note: the data do not include unused post-harvest technologies.

Source: Cooperative Promotion Department (2020a), Ministry of Industry (2020)

B. The spillover effect of marketing cooperatives using a restricted sample

Table B1: The spillover effect of marketing cooperatives using "Selling best quality" sample

	Dependent variable: Log (price received)		
Estimation method	OLS	OLS	2SLS
	(1)	(2)	(3)
Independent variables			
Selling in treated areas	0.146***	0.112***	0.118***
	[0.016]	[0.024]	[0.023]
Selling quantity	0.004*		
	[0.002]		
Selling wet paddy	–0.180***		
	[0.017]		
Selling to miller	0.034*		
	[0.015]		
Selling the best quality	–		
Selling pure variety	0.135***		
	[0.015]		
Selling in January	–0.003		
	[0.041]		
Selling in February	–0.096		
	[0.070]		
Selling in March	–0.094**		
	[0.039]		
Selling in April	–0.069		
	[0.039]		
Selling in May	–0.097**		
	[0.036]		
Selling in June	–0.046		
	[0.032]		
Selling in October	–0.136***		
	[0.018]		
Selling in November	–0.110**		
	[0.038]		
Selling in December	–0.166*		
	[0.079]		
Age	–0.001		
	[0.001]		
Male	–0.007		
	[0.007]		
Education	–0.003		
	[0.002]		
Farm size	0.000		
	[0.000]		
Household Size	0.003		
	[0.008]		
Number of millers	-0.016		
	[0.010]		
Milling capacity	0.005		
	[0.004]		
Observations	179	179	179
R–squared	0.660	0.161	0.160
First stage F–statistic			171.9

Notes: The figures in brackets below the estimates are the standard errors, clustered by cooperatives. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

Table B2: The spillover effect of marketing cooperatives using “Selling to miller” sample

	Dependent variable: Log (price received)		
Estimation method	OLS	OLS	2SLS
	(1)	(2)	(3)
Independent variables			
Selling in treated areas	0.110***	0.068	0.071**
	[0.018]	[0.037]	[0.033]
Selling quantity	0.004		
	[0.002]		
Selling wet paddy	–0.115***		
	[0.022]		
Selling to miller	–		
Selling the best quality	0.088***		
	[0.014]		
Selling pure variety	0.088**		
	[0.034]		
Selling in January	0.058**		
	[0.022]		
Selling in February	–0.112***		
	[0.013]		
Selling in March	–0.025		
	[0.015]		
Selling in April	–0.023		
	[0.031]		
Selling in May	0.017		
	[0.028]		
Selling in June	0.020		
	[0.020]		
Selling in October	–0.114**		
	[0.034]		
Selling in November	–0.094**		
	[0.035]		
Selling in December	–0.142**		
	[0.041]		
Age	0.000		
	[0.001]		
Male	–0.008		
	[0.012]		
Education	–0.001		
	[0.004]		
Farm size	0.000		
	[0.000]		
Household Size	0.002		
	[0.003]		
Number of millers	–0.017**		
	[0.006]		
Milling capacity	0.008**		
	[0.003]		
Observations	203	203	203
R–squared	0.583	0.063	0.063
First stage F–statistic			407.2

Notes: The figures in brackets below the estimates are the standard errors, clustered by cooperatives. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

Table B3: the spillover effect of marketing cooperatives using “Selling to trader” sample

	Dependent variable: Log (price received)		
Estimation method	OLS	OLS	2SLS
	(1)	(2)	(3)
Independent variables			
Selling in treated areas	0.136***	0.096*	0.119***
	[0.025]	[0.048]	[0.042]
Selling quantity	0.006		
	[0.005]		
Selling wet paddy	–0.155**		
	[0.054]		
Selling to miller	–		
Selling the best quality	0.076**		
	[0.030]		
Selling pure variety	0.069		
	[0.037]		
Selling in January	0.025		
	[0.067]		
Selling in February	–0.073		
	[0.064]		
Selling in March	–0.045		
	[0.067]		
Selling in April	–0.016		
	[0.031]		
Selling in May	–0.059		
	[0.069]		
Selling in June	–0.077		
	[0.055]		
Selling in October	–0.200**		
	[0.079]		
Selling in November	–0.143		
	[0.099]		
Selling in December	–0.170		
	[0.115]		
Age	–0.002*		
	[0.001]		
Male	–0.007		
	[0.020]		
Education	0.001		
	[0.004]		
Farm size	–0.001		
	[0.001]		
Household Size	0.004		
	[0.007]		
Number of millers	–0.025*		
	[0.011]		
Milling capacity	0.008		
	[0.005]		
Observations	116	116	116
R–squared	0.664	0.070	0.066
First stage F–statistic			120.2

Notes: The figures in brackets below the estimates are the standard errors, clustered by cooperatives. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

Table B4: The spillover effect of marketing cooperatives using "Selling wet paddy" sample

	Dependent variable: Log (price received)		
Estimation method	OLS	OLS	2SLS
	(1)	(2)	(3)
Independent variables			
Selling in treated areas	0.119***	0.110***	0.112***
	[0.012]	[0.024]	[0.021]
Selling quantity	0.004**		
	[0.002]		
Selling wet paddy	–		
Selling to miller	0.024		
	[0.017]		
Selling the best quality	0.082***		
	[0.019]		
Selling pure variety	0.067**		
	[0.026]		
Selling in January	–		
Selling in February	–		
Selling in March	–		
Selling in April	–		
Selling in May	–		
Selling in June	–		
Selling in October	0.023		
	[0.047]		
Selling in November	0.041		
	[0.049]		
Selling in December	–		
Age	–0.001		
	[0.002]		
Male	–0.011		
	[0.010]		
Education	0.000		
	[0.003]		
Farm size	–0.000		
	[0.000]		
Household Size	–0.002		
	[0.005]		
Number of millers	–0.016*		
	[0.007]		
Milling capacity	0.010*		
	[0.004]		
Observations	217	217	217
R–squared	0.450	0.182	0.182
First stage F–statistic			110.4

Notes: The figures in brackets below the estimates are the standard errors, clustered by cooperatives. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

Table B5: The spillover effect of marketing cooperatives using "Selling in November" sample

	Dependent variable: Log (price received)		
Estimation method	OLS	OLS	2SLS
	(1)	(2)	(3)
Independent variables			
Selling in treated areas	0.133***	0.127***	0.124***
	[0.030]	[0.036]	[0.033]
Selling quantity	0.002		
	[0.001]		
Selling wet paddy	–0.137**		
	[0.042]		
Selling to miller	0.013		
	[0.021]		
Selling the best quality	0.088***		
	[0.019]		
Selling pure variety	0.070		
	[0.052]		
Selling in January	–		
Selling in February	–		
Selling in March	–		
Selling in April	–		
Selling in May	–		
Selling in June	–		
Selling in October	–		
Selling in November	–		
Selling in December	–		
Age	–0.000		
	[0.001]		
Male	–0.017		
	[0.013]		
Education	–0.000		
	[0.003]		
Farm size	0.000		
	[0.000]		
Household Size	0.002		
	[0.003]		
Number of millers	–0.027***		
	[0.005]		
Milling capacity	0.011*		
	[0.005]		
Observations	190	190	190
R–squared	0.466	0.185	0.185
First stage F–statistic			112.1

Note: The figures in brackets below the estimates are the standard errors, clustered by cooperatives. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

Table B6: the spillover effect of marketing cooperatives using single miller in the area sample

	Dependent variable: Log (price received)		
Estimation method	OLS	OLS	2SLS
	(1)	(2)	(3)
Independent variables			
Selling in treated areas	0.159**	0.088	0.099**
	[0.047]	[0.047]	[0.039]
Selling quantity	0.004***		
	[0.000]		
Selling wet paddy	–0.146**		
	[0.044]		
Selling to miller	–0.001		
	[0.015]		
Selling the best quality	0.090***		
	[0.017]		
Selling pure variety	0.077		
	[0.053]		
Selling in January	0.083***		
	[0.020]		
Selling in February	–0.021		
	[0.038]		
Selling in March	–0.032		
	[0.023]		
Selling in April	–0.004		
	[0.029]		
Selling in May	0.002		
	[0.033]		
Selling in June	–0.011		
	[0.040]		
Selling in October	–0.128**		
	[0.044]		
Selling in November	–0.091		
	[0.048]		
Selling in December	–0.120*		
	[0.050]		
Age	–0.001		
	[0.001]		
Male	0.009		
	[0.009]		
Education	–0.002		
	[0.001]		
Farm size	–0.000		
	[0.000]		
Household Size	0.004		
	[0.003]		
Number of millers	–		
Milling capacity	–0.010		
	[0.013]		
Observations	240	240	240
R–squared	0.638	0.078	0.077
First stage F–statistic			96.3

Note: The figures in brackets below the estimates are the standard errors, clustered by cooperatives. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

Table B7: The spillover effect of marketing cooperatives using "Selling the best quality wet paddy to miller in November" sample

	Dependent variable: Log (price received)		
Estimation method	OLS	OLS	2SLS
	(1)	(2)	(3)
Independent variables			
Selling in treated areas	0.156***	0.156***	0.161***
	[0.020]	[0.035]	[0.033]
Selling quantity	–0.002		
	[0.002]		
Selling wet paddy	–		
Selling to miller	–		
Selling the best quality	–		
Selling pure variety	0.178***		
	[0.023]		
Selling in January	–		
Selling in February	–		
Selling in March	–		
Selling in April	–		
Selling in May	–		
Selling in June	–		
Selling in October	–		
Selling in November	–		
Selling in December	–		
Age	–0.001		
	[0.001]		
Male	–0.039**		
	[0.013]		
Education	–0.007		
	[0.004]		
Farm size	0.002**		
	[0.001]		
Household Size	–0.004		
	[0.008]		
Number of millers	–0.028*		
	[0.014]		
Milling capacity	0.011		
	[0.008]		
Observations	59	59	59
R–squared	0.584	0.432	0.432
First stage F–statistic			72.1

Notes: The figures in brackets below the estimates are the standard errors, clustered by cooperatives. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

Q. Questionnaire

1. Identification

I1	Code:	I2	Province:
I7	Location code:	I7	Name:

2. General Information

G1	Household number	G2	Age
G3	Education	G4	Gender ☐ Male ☐ Female
G5	Phone number	G6	Type of Phone ☐ Normal ☐ Smart Phone
G7	Were you born in this village? ☐ Yes ☐ No (Answer G8-G9)	G8	How long have you been in this village?
G9	Where were you born?	G10	Do you speak any language other than Central Thai at home? If yes, what is this language?". ☐ Lao Isan ☐ Khmer ☐ Others
G11	Do you work off-farm? ☐ Yes ☐ No	G12	What are the types of work? ☐ General employment ☐ Trading ☐ Construction ☐ Others
G13	When do you do off-farm work? ☐ After harvesting ☐ All year round ☐ Uncertainty	G14	Does anyone who usually lives in this household own________________ ? If so, how many? (recode 0 if none, the number owned otherwise)

Assets		Assets		Assets	
Walking Tractor		Pump		Pickup car	
Large four-wheel tractor		crop storage buildings		Motorcycle	
Combine harvester		Large four-wheel car		other large buildings for livestock	

3. Jasmine rice cultivation

C1	How much Rai (land unit in Thailand) did your household cultivate during the past 12 months?	C2	What do you grow? ☐ Jasmine rice ☐ Glutinous rice ☐ Others
C3	Jasmine rice planted area	C4	How many years have you grown Jasmine rice?

	Plot	1	2
C5	Land size	Rai	Rai
C6	Type of land holding	☐ Self-owned ☐ Rented ☐ Others	☐ Self-owned ☐ Rented ☐ Others
C7	What type of land certificate covers this plot?	☐ SK1 ☐ NS.3 ☐NS.3K, ☐ NS.4 ☐ Deed	☐ SK1 ☐ NS.3 ☐NS.3K, ☐ NS.4 ☐ Deed
C8	What is the distance from your dwelling to the furthest rice field?		
C9	Location	Lat Long	Lat Long
C10	How was this plot acquired?	☐ Inherited ☐ Buying ☐ Other	☐ Inherited ☐ Buying ☐ Other
C11	Was this plot inherited from your spouse family?	☐ Yes ☐ No	☐ Yes ☐ No
C12	If yes, how many siblings does the spouse have?		
C13	If no, how many siblings do you have?		
C14	Irrigated	☐ Yes ☐ No	☐ Yes ☐ No
C15	Source of water	☐ Rain ☐ Irrigated water ☐ Ground water ☐ River or pond ☐ Others	☐ Rain ☐ Irrigated water ☐ Ground water ☐ River or pond ☐ Others

C16	Which month did you plant rice?		
C17	Land preparation	☐ Hire ☐ By myself	☐ Hire ☐ By myself
C18	Cost of land preparation		
C19	What type of Jasmine rice varieties that you grow?	☐ Go Kho 15 ☐ Khao Dawk Mali 105	☐ Go Kho 15 ☐ Khao Dawk Mali 105
C20	Planting method	☐ Transplanting ☐ Direct seedling	☐ Transplanting ☐ Direct seedling
C21	Seed used	☐ Buy new seeds ☐ Use old seeds	☐ Buy new seeds ☐ Use old seeds
C22	Seedling method	☐ Machine ☐By hand	☐ Machine ☐By hand
C23	Seedling	☐ Hire ☐ By myself	☐ Hire ☐ By myself
C24	Seedling cost if you hire (per Rai)		
C25	Did you used chemical fertilizers?	☐ Yes ☐ No	☐ Yes ☐ No
C26	How much fertilizers that you used?	Bags	Bags
C27	How did you apply fertilizers?	☐ Machine ☐By hand	☐ Machine ☐By hand
C28	Applying fertilizer	☐ Hire ☐ By myself	☐ Hire ☐ By myself
C29	Did you use pesticide?	☐ Yes ☐ No	☐ Yes ☐ No
C30	Did you use herbicide	☐ Yes ☐ No	☐ Yes ☐ No
C31	Applying pesticide/herbicide	☐ Hire ☐ By myself	☐ Hire ☐ By myself
C32	If you hire, how much?		
C33	Do you use organic matter to improve the soil?	☐ Yes ☐ No	☐ Yes ☐ No
C34	Harvesting months		
C35	Harvesting methods	☐ Machine ☐ Labor	☐ Machine ☐ Labor
C36	Harvesting cost		
C37	Production (ton)		
C38	Yield per Rai		
C39	Keep for household consumption		
C40	Keep for next year planting		

C41	Do you buy rice for household consumption?	☐ Yes ☐ No	☐ Yes ☐ No

4. Jasmine rice marketing

M1	How many rounds you sold Jasmine paddy in marketing year 2018/19?

	Selling round	First round	Second round
M2	Type of paddy sold	☐ Wet ☐ Dry	☐ Wet ☐ Dry
M3	Selling time (month)		
M4	Selling method	☐ Self-transport ☐ Pick up by traders	☐ Self-transport ☐ Pick up by traders
M5	Who do you sell your crop to?	☐ Millers ☐ Traders ☐ Others	☐ Millers ☐ Traders ☐ Others
M6	Do you have price information before selling rice?	☐ Yes ☐ No	☐ Yes ☐ No
M7	How do you get information on rice price?	☐ Neighbors ☐ Telephone ☐ Radio ☐ Others	☐ Neighbors ☐ Telephone ☐ Radio ☐ Others
M8	How long have you been selling to this buyer?		
M9	Name of buyer		
M10	What is the distance from your dwelling to the buyer?		
M11	Why did you decide to sell to this buyer?	☐ Locations near house ☐ Price ☐ Convenient ☐ Trust ☐ Small volume ☐ No transportation ☐ No labor ☐ Others	☐ Locations near house ☐ Price ☐ Convenient ☐ Trust ☐ Small volume ☐ No transportation ☐ No labor ☐ Others

M12	How do you transport your rice to buyers?	☐ Own car ☐ Hiring ☐ Others	☐ Own car ☐ Hiring ☐ Others
M13	Selling quantity (ton)		
M14	Quality		
M15	Moisture content		
M16	Price (baht per kilogram)		
M16A	Did you receive the announced price?	☐ Yes ☐ No	☐ Yes ☐ No
M16.1	How much cash did you receive from this transaction?		
M16.2	Do you have mixed rice varieties problem?	☐ Yes ☐ No	
M17	Do you negotiate when selling rice? ☐ Yes ☐ No	M18	If yes, how much the price increase?
M19	Did you know the buying price of coop? ☐ Yes ☐ No	M20	What is the price difference between coops and private intermediaries?
M21	Why you did not sell rice to coops? ☐ Far away ☐ Not receive cash immediately ☐ Not convenient ☐ Others		
M24	Do you know the retail price of Jasmine rice? ☐ Yes ☐ No	M25	Do you know the export price of Jasmine rice? ☐ Yes ☐ No

Chapter 4 The market-level effect of large-scale on-farm storage intervention: Evidence from Thailand

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Abstract

In local markets, interventions on some individuals may generate market-level effects. This paper evaluates the effect of large-scale on-farm storage intervention that relaxes credit constraints at harvest-time on local market prices. Because the change in local supply or on-farm storage under the intervention is not random, we employ two econometric strategies. First, we convert our variables to first differences. We then instrument the differenced on-farm storage quantity under the intervention using 4-year, and 5-year lagged on-farm storage. Using 18 years of panel data from 19 provinces in Thailand, our instrumental variable estimates indicate that the decrease in local supply caused by on-farm storage intervention significantly affects local rice market price. In contrast, we find that the local supply change caused by the intervention cannot stabilize price inter-seasonally. Our findings provide crucial evidence for policy debates regarding the welfare implications of on-farm storage interventions when delivered on a massive scale.

Keywords: On-farm storage**,** Thailand, Jasmine rice, Local market price, Instrumental variable

4.1 Introduction

On-farm grain storage is one of the most critical strategies that smallholder farmers use to optimize selling times and avoid seasonal hunger caused by the seasonality of agriculture. However, despite the desire to store grains, many farmers in developing countries are forced to sell their crops immediately after harvest because of credit constraints (e.g., Stephens and Barrett, 2011) and storage technology constraints (e.g., Aggarwal et al., 2018) . To relax these constraints, international donors, development agencies, and governments have introduced two types of on-farm storage interventions. The first one is to offer smallholder farmers a loan at harvest, and the second one is to offer farmers free storage technology such as bags and metal silos.

A growing number of studies has been dedicated to understanding the effects of on-farm storage interventions on individual farmers. These studies have shown that on-farm storage interventions have positive and significant impacts on farmers' ability to store (Aggarwal et al., 2018; Burke et al., 2018; Le Cotty et al., 2019; Saak, 2003), nutritional status (Gross et al., 2020), food security (Bokusheva et al., 2012; Brander et al., 2020; Gitonga et al., 2013), technology adoptions (Omotilewa et al., 2018; Ricker-Gilbert and Jones, 2015), and consumptions and income (Basu and Wong, 2015). Nevertheless, little effort has investigated the effects of on-farm storage interventions on equilibrium market prices, even though scaling them will significantly affect local market supply conditions. This lack of research is because, to test the market-level effects rigorously, researchers need to conduct a large-scale experiment, which is costly and challenging to organize. However, understanding these effects is essential when wanting to predict the effects of these interventions would have at scale (de Janvry et al., 2017).

We hope to fill this knowledge gap from a non-experimental setting. Specifically, we seek to answer the following two questions: First, does the change in local supply caused by on-farm storage interventions affect equilibrium market prices? Second, is this change in supply able to stabilize price inter-seasonally? To answers these questions, we first develop a simple model to illustrate how on-farm storage interventions affect farmer storage decisions and how the aggregation of individual storage decisions affects the local market equilibrium.

We then test the model by examining a large-scale on-farm storage intervention[53] that offers farmers a harvest-time cash loan in 19 local rice markets in Thailand. We believe the on-farm storage intervention in Thailand is an ideal setting because of the scale of intervention, data set availability, and empirical identification strategy it affords.

Estimating the effects of the change in local supply caused by on-farm storage interventions on local market prices in a non-experimental setting must address two critical issues that complicate the analysis. The first issue is heterogeneity bias that arises because farmers' decisions to participate in the program are likely to relate to farmer characteristics and local area characteristics. As a result, part of the observed market price differences between areas with the different amounts of on-farm storage under the intervention may, either totally or partially, reflect the fundamental difference between them, rather than the effect of the intervention. The second issue is reverse causality, where local market prices are related to farmers' decisions to participate in the program. These issues or endogeneity make it very difficult to establish causality using observational data.

We attempt to tackle the endogeneity issue by using econometric strategies similar in spirit to that used by Goldberg and Pavcnik (2005) and Ahsan and Mitra (2014) to examine the impact of trade reforms. In particular, we first convert our variables to first difference. We then instrument the differenced on-farm storage quantity under the intervention (it represents the local supply change caused by the intervention) using 4-year and 5-year lagged on-farm storage quantity. The argument for our instrument's validity is that the differenced on-farm storage quantity term is likely to correlate with 4-year and 5-year lagged on-farm storage quantity because of autocorrelation. Moreover, given the time difference between the differenced error term and our instrument variables, we believe that they are sufficiently far removed from each other and are therefore unlikely to be correlated.

Our instrumental variable estimates suggest that the change in local market supply induced by on-farm storage intervention at harvest significantly affect local market equilibrium. For example, an increase in on-farm storage quantity under the intervention by 20,000 tons,

[53] Since 1982, the state-own agricultural development bank has allowed rice farmers to borrow by keeping paddy in storage facilities on their farms as collateral.

which implies 20,000 tons of local supply contraction, causes the farm gate price of rice in November to increase by 1.31%. Moreover, we find that the local supply change caused by the harvesting period's intervention also significantly affects local farm gate price during the non-harvesting period. For instance, the intervention causes the farm gate price in April (3 month after the intervention) to increase by 1.16%. On the other hand, we find that the change in local supply caused by the intervention cannot stabilize price inter-seasonally in our settings.

Our research contributes to the empirical literature on the impact of on-farm storage interventions. To the best of our knowledge, this is the first study that provides evidence of market-level effects of on-farm storage interventions by exploiting the advantage of panel data. Significant progress has been made in estimating the impacts of on-farm storage interventions at the individual-level (e.g., Aggarwal et al., 2018; Basu and Wong, 2015). However, little progress has been made in estimating its market-level effects[54]. To the best of our knowledge, only Burke et al. (2018) have evaluated the market-level effect or general equilibrium effect of on-farm storage intervention (offering farmers a harvest-time cash loan) in developing countries. They experimentally varied the density of loan across 17 locations in Kenya. They find that increased on-farm storage at the market level (induced by the credit intervention) significantly affects local maize market prices during the harvesting period, but not during the non-harvesting period.

Our study is complementary to Burke et al.'s study in three critical ways. First, Burke et al. (2018) use randomized controlled trials as their methodology to exogenize the level of local supply change and observe the market-level effect of on-farm storage intervention. In contrast, we apply two econometric strategies (first difference and instrumental variable methods) to exogenize the level of local supply change induced by the intervention in order to

[54] Prior studies use US data and simulation models to examine the market-level effect of on-farm storage interventions (Lence and Hayes, 2002; Westcott and Price, 2001). For example, Lence and Hayes (2002) use simulation model to evaluate the long-term impact of marketing loan programs (loan rate program and loan deficiency payment) under the Federal Agricultural Improvement and Reform Act of 1996. They find that these two programs have no significant long-term impact on market price and farmers' income.

detect its market-level effect. Second, unlike Burke et al.[55], we use a continuous variable (on-farm storage quantity under the intervention) for identification. This allows us to capture the impact of on-farm storage intervention on local supply and show the extent to which a reduction in local supply would change the equilibrium prices. To the best of our knowledge, this is the first study to assess the effect of on-farm storage intervention on market equilibrium using continuous variables. Finally, we provide the validation of the market-level effect of on-farm storage interventions in a different setting.

To assess the credibility of our results, we perform a placebo analysis by replicating the primary analysis with the outcome replaced by Japanese retail rice prices (pseudo outcomes). The placebo tests indicate that our results are credible. Moreover, our results are robust to a different way of instrumenting, different estimation methods, the inclusion of other independent variables, and the exclusion of outliers. Our results provide two crucial implications for evaluators and policymakers. First, the economic impact assessment of on-farm storage interventions needs to include its market-level effect. This implication is also applied to the assessment of any technological or infrastructure investments that will improve farmers' ability to store. Second, on-farm storage interventions, when delivered at scale, can be used as an effective tool to enhance the local farm gate prices. This implication is beneficial for governments seeking to prevent the falling local farm gate prices due to excess supply at harvest.

The remainder of the paper is structured as follows. The next section describes the empirical setting. The section following presents the conceptual framework and the empirical strategy. We then illustrate data used in the analysis, followed by estimation results and implication for policy and evaluation. The last section concludes.

[55] They use treatment intensity as a proxy for change in local supply.

4.2 Background

4.2.1 On-farm storage interventions in developing countries

A growing empirical study has shown that smallholder farmers in developing countries are forced to sell at harvest, when prices are low, because of credit and liquidity constraints and technology constraints (e.g. Aggarwal et al., 2018; Dillon, 2020; Kadjo et al., 2018; Stephens and Barrett, 2011). As a result, they are forced to forgo many potential benefits from on-farm storage, such as ensuring household food supplied, saving for future cash needs, and choosing the best selling time. For example, poor households in Malawi missed out on an expected 17.3-26.5% increase in crop prices over three months because they are forced to sell crops early to finance their children's education (Dillon, 2020).

Given the potential benefits of on-farm storages, two types of intervention have been developed and rigorously tested for their benefits. The first type of intervention is to offer farmers a loan at harvest (Basu and Wong, 2015; Burke et al., 2018). For example, an experimental study from Kenya shows that providing smallholder farmers with the loan at harvest significantly decreases the amount of maize sold at harvest. This change in their marketing behavior leads to an increase in revenue by 29% (Burke et al., 2018). The second type of intervention is to offer farmers an improved storage technology (Aggarwal et al., 2018; Bokusheva et al., 2012; Brander et al., 2020; Gitonga et al., 2013; Omotilewa et al., 2018). These technologies, such as bags and metal silos, will significantly reduce storage losses due to factors such as molds and rats, which in turn will reduce storage costs. Consequently, farmers are more likely to store crops after harvest. For instance, an experimental study from Uganda shows that providing smallholder farmers with one hermetic storage bag significantly extends storage duration (Omotilewa et al., 2018). Overall, prior studies have shown that on-farm storage interventions can increase storage quantity at harvest. As a result, on-farm storage intervention, when delivered at scale, will significantly change local supply conditions. Theoretically, these changes are expected to affect local market prices. However, little is known about the impact of on-farm storage interventions on local market prices. This lack of research is partly due to the difficulty in organizing large-scale experiments and in identifying causal effects from non-experimental settings.

4.2.2 "The Farmer Loans to Delay the Sales of Rice Paddy" program in Thailand

The Farmer Loans to Delay the Sales of Rice Paddy program or On-farm Paddy Pledging program in Thailand is designed to provide soft loans for farmers who would like to delay their paddy (unmilled rice) sales. This program was first introduced in 1982. Under this program, the state-owned agricultural bank or Bank for Agriculture and Agricultural Cooperatives (BAAC) offers farmers a harvest-time cash loan. Farmers can borrow from BAAC by keeping their paddy on-farm as collateral. The loan value equals a pledge price times on-farm storage quantity. The pledge price and the maximum loan value per household are set yearly by the Rice Policy Committee (chaired by the Prime Minister). Each loan carries a "flat" interest rate of 0%[56] to 3%, with full repayment due after four to five months. If farmers decide not to repay the loan, the bank agrees to accept paddy as full payment for an outstanding loan. To apply for the loan, farmers must contact the branch of BAAC in their district. BAAC officers will then visit farmers' storage facility to check the quality and the amount of paddy. After that, the loan will be transferred to the farmers' bank account with BAAC. Figure 4.1 shows the loan value or pledging price per ton, the farm gate price, and the percentage of national aggregate on-farm storage quantity (Jasmine paddy) under on-farm storage intervention to total production during our sample periods. Between the marketing years[57] 2001/02 to 2008/09 and between 2011/12 to 2013/14, the loan value was set relatively high compared to the farm gate price. In contrast, after the marketing year 2013/14, the loan value was set close to or below the farm gate price.

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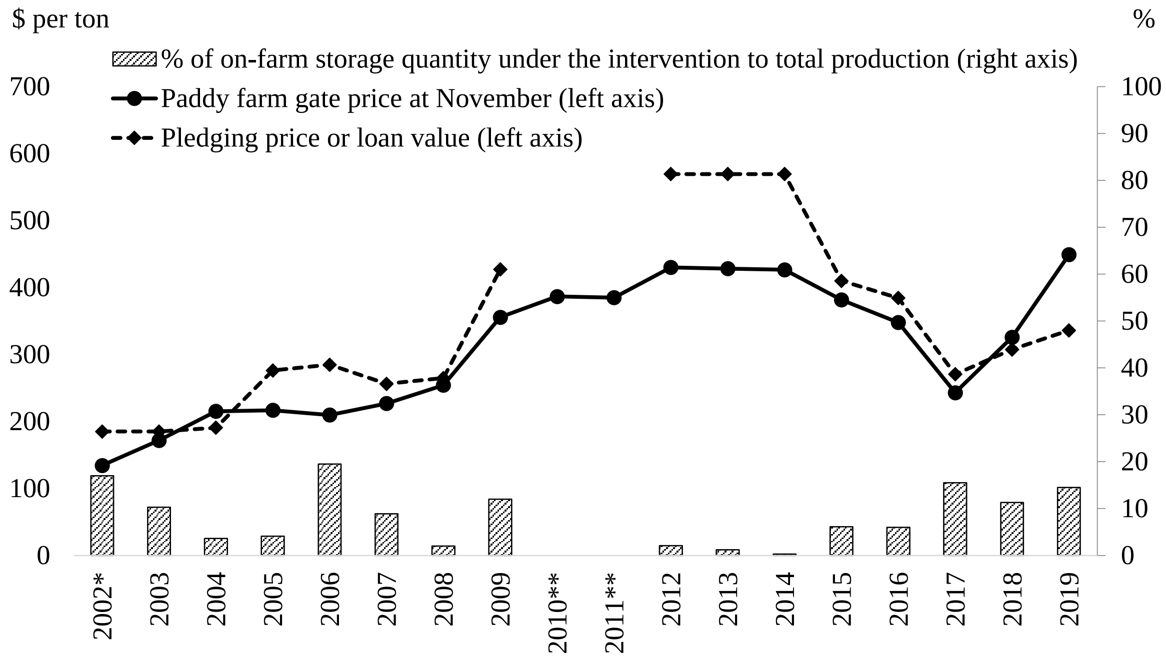
[56] In some year, the government offer full subsidy for interest rate.

[57] We define marketing year 2001/02 as October 1, 2001 to September 31, 2002.



Note: *Marketing year 2001/02, ** No on-farm storage intervention

Figure 4.1: The farm gate price (nominal price), loan value, and % of on-farm storage quantity (Jasmine paddy) under on-farm storage intervention

The on-farm storage intervention in Thailand provides an ideal setting to measure the market-level effects of the intervention because it has been implemented on a nationwide scale with as much as 212,000 participating farmers over a long period of time (more than 20 years). Thus, the intervention generates a substantial shock to the local supply of rice. This generated supply shock is relevant for any on-farm storage intervention that succeeds in improving farmers' ability to store.

4.3 Conceptual framework

4.3.1 A model of farmer storage decisions under on-farm storage interventions

To illustrate how on-farm storage interventions could affect farmer storage decisions, consider location A populated by risk-neutral farmers who have rice surplus for sale. Suppose each cropping year consists of two periods, harvesting (t) and non-harvesting ($t+1$). After realizing their rice surplus at the harvesting period, each individual farmer decides whether to sell rice immediately or store rice for sale in the non-harvesting period. The farmers' objective is to maximize profit from selling their surplus rice. Let P_t denotes farm gate price per ton at period t and let $E_t(P_{t+1})$ denotes expected (E) future price that farmers anticipate at period t. Suppose the expected discounted future price is $\frac{E_t(P_{t+1})}{1+r}$ where r is the interest rate, and suppose $\frac{E_t(P_{t+1})}{1+r} > P_t$. The costs of storing rice from period t to period $t+1$ are denoted k. These costs include grain loss caused by several factors such as adverse weather and micro-organisms.

We begin by assuming that there are no on-farm storage interventions. Following the competitive rational storage model (e.g., Deaton and Laroque, 1996; Williams and Wright, 1991), an individual farmer decides not to store rice for sale in the next period if the storage costs are higher than the expected gain from storing rice, i.e., $k > \frac{E_t(P_{t+1})}{1+r}$ - P_t. In this case, the farmer could not take advantage of inter-seasonal price volatility due to high storage costs. However, even $\frac{E_t(P_{t+1})}{1+r} - P_t > k$, he/she will also decide not to store rice if he/she needs to use cash during the harvesting period. In this case, the farmer is forced to forgo the gain from storage because of credit constraints.

Next, suppose two types of on-farm storage interventions are introduced to location A. The first one is to offer farmers free storage technology such as bags and metal silos. Under this intervention, the storage costs for farmers who adopt a better storage system will reduce from k to $k^{/}$. As a result, the farmer will decide to store rice if $\frac{E_t(P_{t+1})}{1+r} - P_t > k^{/}$. The second type of intervention is to offer farmers a loan at harvest and ask them to keep their paddy on-farm as collateral. Suppose the farmer must repay L by the end of the loan period. The farmer will take up the loan if the expected discounted future price minus the storage costs are greater than the outstanding loan, $\frac{E_t(P_{t+1})}{1+r} - k > L$. In this case, the farmer will gain $\left(\frac{E_t(P_{t+1})}{1+r} - k\right) - L$ from participating in the credit intervention.

Now, let ofs_{niy} is the on-farm storage quantity under the interventions of a farmer n at location i, and year y. Thus, the aggregation of on-farm storage quantity or the change in local supply caused by the interventions is

$$OFS_{iy} = \sum_{all\ n} ofs_{niy}$$

when n is small, OFS_{iy} may not affect the market equilibrium. However, when n increases because of the expansion of the interventions, OFS_{iy} could affect the local rice market equilibrium.

4.3.2 The market-level effect of on-farm storage intervention

This part considers how individual-level on-farm storage intervention through the credit intervention could affect local rice market equilibrium in each location. We modified the rational storage model of Carter, Rausseer, and Smith (CRS) (2016) to our setting. CRS model focuses on annual variation and *inter-year* carryover from the end of one crop year to the beginning of the next. In contrast, our model focuses on seasonal variation and *intra-year* carryover from the harvesting period to the non-harvesting period. Three integrated markets determine the equilibrium level of inventory held by firms in the storage industry (exclude on-farm storage): (1) supply and demand for use in the harvesting period (*t*); (2) expected supply and demand in the non-harvesting period (*t+1*); (3) storage from the harvesting period to the non-harvesting period. We begin by assuming that there are no on-farm storage interventions. Figure 4.2 illustrates the equilibrium for a case with linear supply and demand. Assume that the rice supply and demand at period *t* are S_t and D_t, respectively.

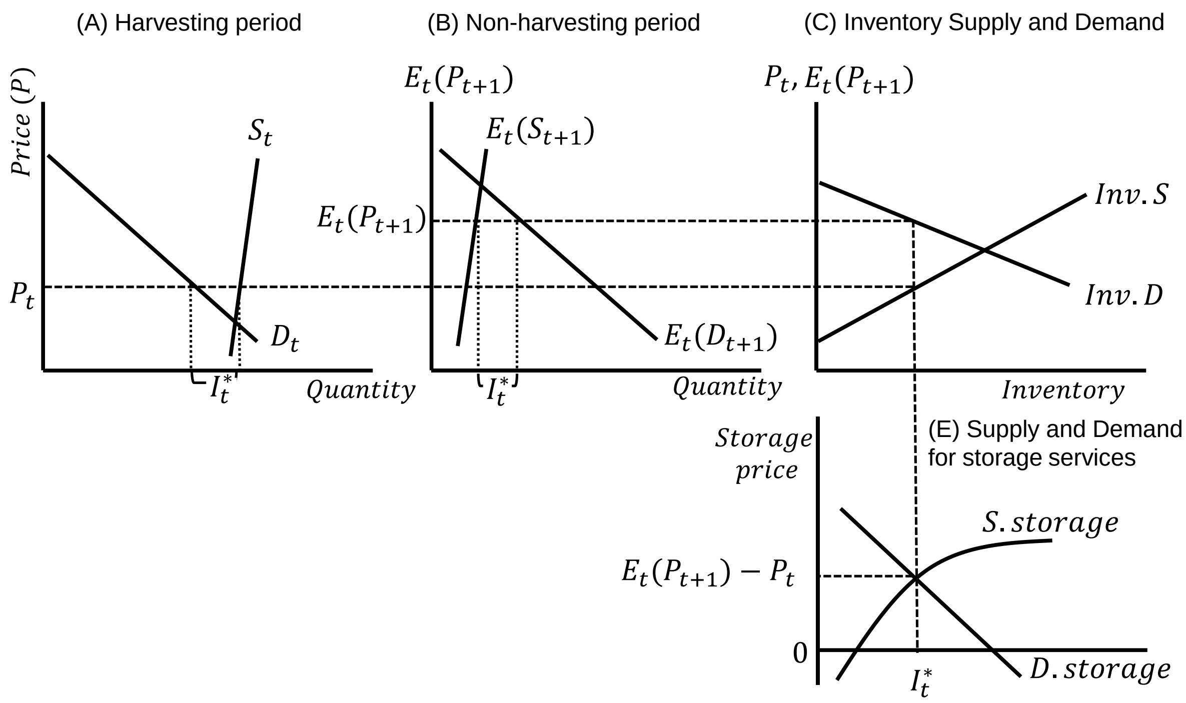
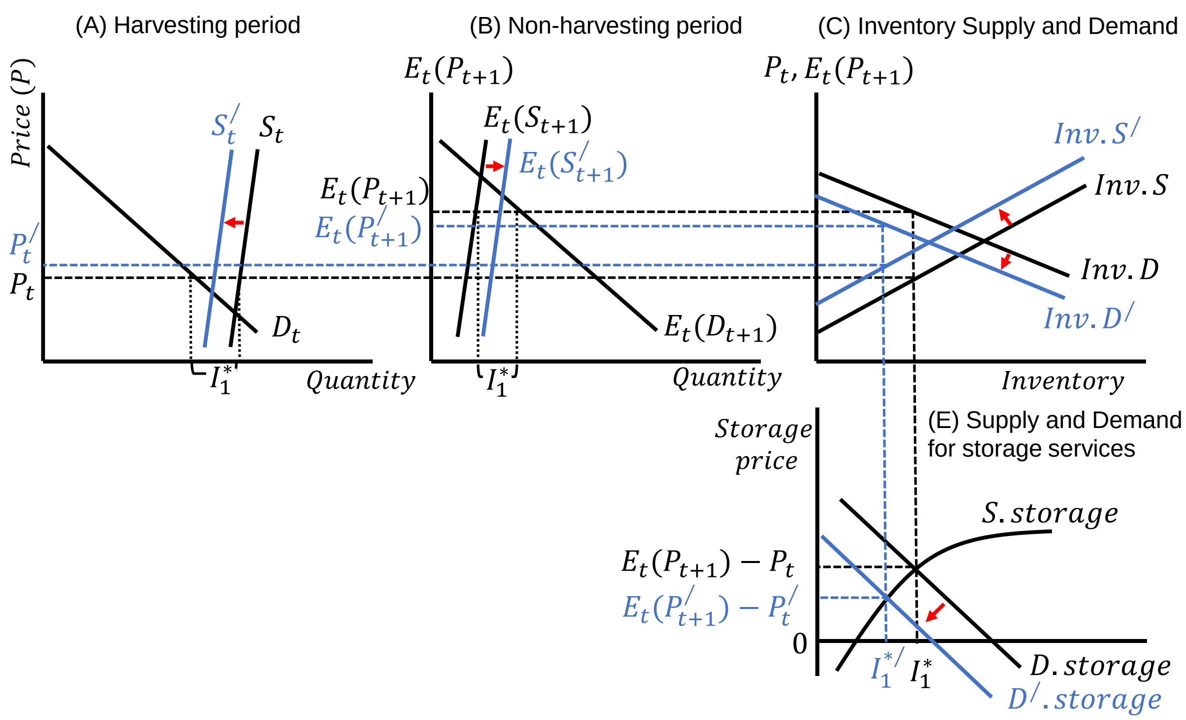


Figure 4.2: Two-periods commodity-market equilibrium

Panel A of Figure 4.2 shows the period *t* supply and demand curve. Panel B shows the period *t+1* demand and supply curve. Assume that the rice supply and demand at period *t+1* are S_{t+1} and D_{t+1}. Panel C shows the inventory supply and inventory demand curve. The inventory supply is equal to the horizontal difference between supply and demand curves in period *t.* In contrast, the inventory demand is equal to the horizontal gap between the supply and demand curve in period *t+1*. As the inventory supply curve is evaluated at the period *t* spot price P_t and the inventory demand curve is evaluated at the expected period *t+1* spot price $E_t(P_{t+1})$, the vertical difference between these curves equals the demand for storage. The market will clear at the intersection of inventory supply and inventory demand curves only if the market price of storage is zero, i.e., $E_t(P_{t+1}) - P_t = 0$. Panel E illustrates demand and supply for storage. We depict the supply of storage as linear in the log of inventory. The intersection of the supply for storage curve and the demand for storage curve determines the equilibrium level of inventory (I_t^*).

Now, suppose on-farm storage intervention that offer farmers a loan at harvest is introduced to location A. The effects of this on-farm storage intervention on market equilibrium depend on the loan repayment behaviors of participating farmers. Panel F in Figure 4.3 shows the effect of the change in local supply caused by on-farm storage intervention on market equilibrium when all participating farmers repay the loan by selling paddy to the market at period *t+1*. The intervention causes the supply curve in period *t* to shift to the left from S_t to $S_t^{/}$ because, at any given price, the intervention induces farmers to supply less paddy in period *t* than they did before the intervention. Since on-farm storage under the intervention will be sold by participating farmers in order to get money to repay the loan in period *t+1*, the supply curve in this period shifts to the right from S_{t+1} to $S_{t+1}^{/}$. As a result, the intervention shifts the supply of inventory curve and the inventory demand curve in panel C to the left, which in turn shifts the demand for the storage curve in panel E to the left. The intervention causes the equilibrium level of inventory to decrease from I_t^* to $I_t^{*/}$, the equilibrium price at period *t* to increase from P_t to $P_t^{/}$, the expected price in period *t+1* to reduce from $E_t(P_{t+1})$ to $E_t(P_{t+1}^{/})$, and the intra-year price difference to reduce from $E_t(P_{t+1}) - P_t$ to $E_t(P_{t+1}^{/}) - P_t^{/}$.

(F) The effect of the intervention when farmers repay the loan



(G) The effect of the intervention when farmers forfeit their paddy to the bank

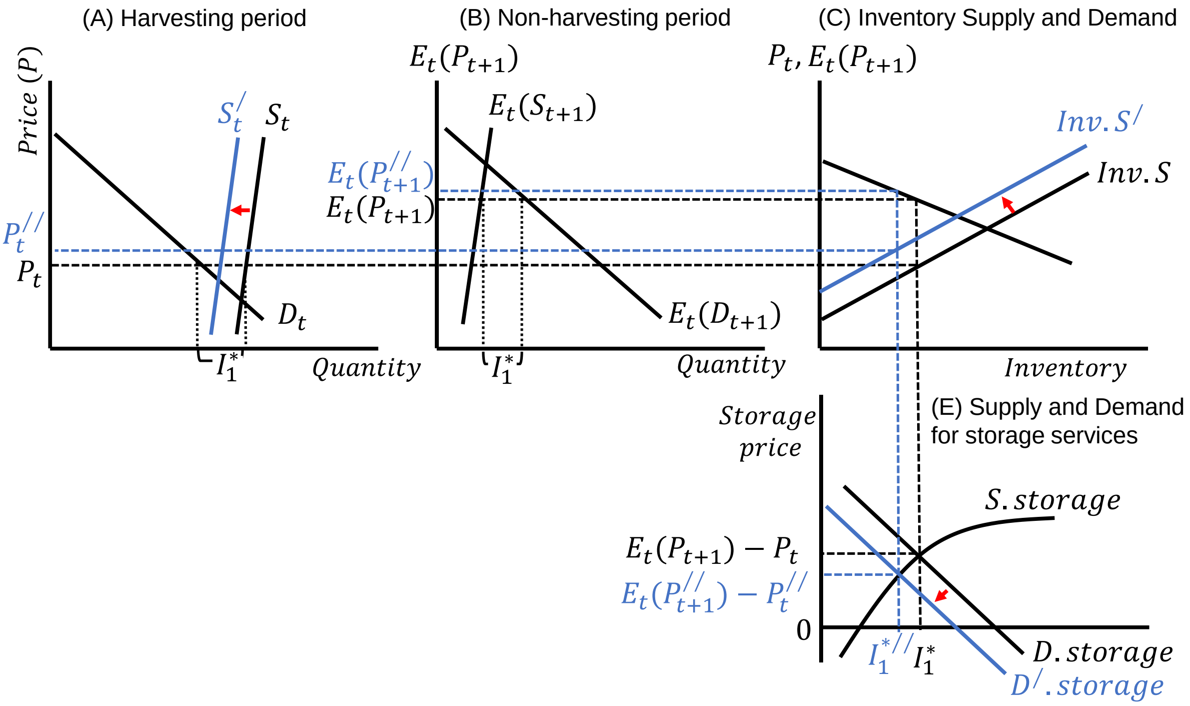


Figure 4.3: The effect of the change in local supply cuased by on-farm storage intervention on market equilibrium

Panel G in Figure 4.3 shows the effect of the on-farm storage intervention when all participating farmers do not repay the loan by forfeiting their paddy to the state-owned bank (BAAC). Unlike Panel F, the supply curve in period *t+1* does not shift because farmers do not sell their paddy under the intervention to the local market in period *t+1* as they decide to forfeit their paddy to the bank, and the bank does not sell[58] paddy to the local market in period *t+1*. As a result, the intervention shifts only the supply of inventory curve in panel C to the left, which in turn shifts the demand for the storage curve in panel D to the left. The intervention causes the equilibrium level of inventory to decrease from I_t^* to $I_t^{*//}$, the equilibrium price at period *t* to increase from P_t to $P_t^{//}$, the expected price in period *t+1* to increase from $E_t(P_{t+1})$ to $E_t\left(P_{t+1}^{//}\right)$, and the intra-year price difference to reduce from $E_t(P_{t+1}) - P_t$ to $E_t\left(P_{t+1}^{//}\right) - P_t^{//}$. In sum, regardless of the loan repayment behavior of participating farmers, we would expect the intervention to increase the market prices during the harvesting period and

[58] The committee for releasing paddy under the intervention will decide when and where to sell the forfeited paddy.

reduce the variance of prices in local markets. In contrast, the effect of the intervention on the local market price during the non-harvesting period will depend on the loan repayment behavior of participating farmers. If farmers repay the loan, we expect the intervention to reduce the market prices during the non-harvesting period. On the contrary, if farmers do not repay the loan, we expect the intervention to increase the market prices during the non-harvesting period.

4.4 Empirical strategy

4.4.1 Empirical specification

To estimate the effect of the change in local supply caused by on-farm storage intervention on the local farm gate price of paddy, consider a simple unobserved or fixed-effects model:

$$\log(P_{imy}) = \beta_0 + \phi_1 OFS_{iy} + a_i + \gamma_y + \epsilon_{imy} \quad (4.1)$$

where P_{imy} is the farm gate price of Jasmine paddy at province *i* in month *m* (1 = January, …, 12 = December) in marketing year *y*, OFS_{iy} is on-farm storage quantity under the intervention: it represents the change in local supply caused by the intervention, a_i is an unobserved effect or a province fixed effect (time-invariant): it represents all factors affecting the provincial farm gate price that do not change over time, such as the province location and other demographic features of the farmers (education, ability), γ_y is a time fixed effect (province-invariant): it represents all factors affecting the provincial farm gate price that do not change across provinces, such as the pledging price set by the government, and ϵ_{imy} is an idiosyncratic error or time-varying error: it represents unobserved factors such as the number of an on-farm storage facility that change over time and affect P_{imy}. In the harvesting period (October, November, and December), we expect that $\phi_1 > 0$. Since we do not have the data on the loan repayment rate, we expect that $\phi_1 < 0$ if many participating farmers repay the loan, whereas we expect that $\phi_1 > 0$ if many participating farmers do not repay the loan.

Next, to evaluate whether the change in local supply caused by on-farm storage intervention can stabilize price inter-seasonally, consider a simple unobserved effects model:

$$Pvol_{iy} = \beta_1 + \phi_2 OFS_{iy} + a_i + \gamma_y + \mu_{iy} \tag{4.2}$$

where $Pvol_{iy}$ is the farm gate price volatility – here, the coefficient of variation (i.e., standard deviation divided by means) of the farm gate price series over one marketing year – at province i and marketing year y, and μ_{iy} is an idiosyncratic error or time-varying error: it represents unobserved factors that change over time and affect $Pvol_{iy}$. As we expect that the intervention may reduce the farm gate price volatility, we predict that $\phi_2 < 0$.

The regression of Equation 4.1 is unlikely to yield an unbiased estimate of ϕ_1 because of two econometric problems. First, we have heterogeneity bias because provinces with the different amount of on-farm storage under on-farm storage intervention are likely to differ along other dimensions, such as their locations (included in a_i), the level of farmer risk preference, and the number of the on-farm storage facility (included in ϵ_{imy}). As a result, part of the observed farm gate price differences between provinces with the different amounts of on-farm storage may, either totally or partially, reflect the fundamental difference between them, rather than the effect of the intervention. Second, we have a reverse causality problem because the farm gate price can cause changes in the on-farm storage quantity under the intervention. Namely, when the farm gate prices are low (high), the on-farm storage quantity may be high (low) because farmers are more (less) likely to participate in the intervention. These two sources of endogeneity will lead to a biased estimate of ϕ_1.

The regression of Equation 4.2 also faces the same problems as in Equation 4.1 because price volatility is calculated from the farm gate price in Equation 4.1. Therefore, to be successful in estimating the effect of on-farm storage intervention on the farm gate price and the farm gate price volatility, we must overcome the problem of endogeneity.

4.4.2 Identification strategy

We address the endogeneity issue by using econometric strategies similar in spirit to that used by Goldberg and Pavcnik (2005) and Ahsan and Mitra (2014) to examine the impact of trade reforms. Precisely, we first convert Equations 4.1 and 4.2 to first differences and include a dummy variable for each marketing year (M_y). We have

$$\Delta\log(P_{imy}) = \beta_2 + \phi_1 \Delta OFS_{iy} + \delta M_y + \Delta\epsilon_{imy} \quad (4.3)$$

$$\Delta Pvol_{iy} = \beta_3 + \phi_2 \Delta OFS_{iy} + \delta M_y + \Delta\mu_{iy} \quad (4.4)$$

where Δ denotes the change from *y* to *y*+1. Now, the unobserved effect, a_i does not appear in Equations 4.3 and 4.4 because it has been "differenced away," as a_i does not vary with time, i.e., $(a_i - a_i = 0)$. γ_y also disappears as we include a year dummy variable. As a result, we have removed any time-invariant characteristic of provinces and time fixed effects that are correlated with the dependent variables and the on-farm storage quantity under the intervention.

Next, we address reverse causality and remaining bias from omitted variables by using the instrumental variables approach. This approach is widely used to overcome endogeneity problems in causal relationship estimates (Angrist and Krueger, 2001). We instrument ΔOFS_{iy} term using 4-year and 5-year lagged OFS or $OFS_{i,y-4}, OFS_{i,y-5}$. For this IV strategy to be valid, our instrumental variables (IVs) need to satisfy two assumptions. First, IVs need to be correlated with ΔOFS_{iy} (relevance assumption). To illustrate the validity of this assumption, consider Equation 4.3 at *m = 11* or November and period *y* = 6, we have

$$P_{i11,6} - P_{i11,5} = \beta_2 + \phi_1(OFS_{i6} - OFS_{i5}) + \delta M_y + (\epsilon_{i11,6} - \epsilon_{i11,5}) \quad (4.5)$$

Our IVs, OFS_{i2}, OFS_{i1}, are likely to be correlated with $(OFS_{i6} - OFS_{i5})$ term because of dynamic adjustment processes or autocorrelation. For example, if the local branch of the bank (BAAC) in some provinces manages on-farm storage intervention better than others, we would expect the on-farm storage quantity under the intervention to be correlated with the local branch's ability in each province. Since this ability is likely to be carried over to the next years, we would expect the on-farm storage quantity in each province to be correlated across time. Specifically, we have

$$OFS_{i6} - OFS_{i5} = \alpha_2 OFS_{i2} + \alpha_1 OFS_{i1} + (\varepsilon_{i6} - \varepsilon_{i5}) \tag{4.6}$$

where ε_{i6} and ε_{i5} is the error term. As we expect that α_2 and α_1 are not equal to zero, our IVs satisfy relevance assumption.

The second assumption needed for the validity of our IV strategy is that the current differences in the error term or $\Delta\epsilon_{imy}$ is uncorrelated with 4-year and 5-year lagged OFS (exclusion restriction assumption). Given the time difference between the differenced error term and our IVs, we believe that they are sufficiently far removed from each other and are therefore unlikely to be correlated. Nevertheless, our IVs could be correlated with the differenced error term if there is serial correlation in the errors. For instance, consider Equation 4.5, OFS_{i1} will be correlated with $(\epsilon_{i11,6} - \epsilon_{i11,5})$ if OFS_{i1} affects the price in November at period one and the price in November at period one is correlated with the price in November at period two and the price in November at period two is correlated with the price in November at period three and so on (serial correlation). Hence, our IVs will satisfy the exclusion restriction assumption only if there is no serial correlation in the errors. Since it is possible to statistically test for serial correlation in the error terms (Arellano and Bond, 1991), we will rely on this test's results to support the validity of our exclusion restriction assumption.

Another critical assumption underlying our analysis is that there is no spatial correlation[59] in our data. One may concern about the validity of this assumption because of cross-province trade. Namely, the farm gate price at one province may be affected by the farm gate price at the nearby provinces because when there is a price difference between provinces, traders motivated by arbitrage opportunities will facilitate trade between provinces.

[59] If spatial correlation is present it will violate the assumption of the independence of error and make the hypothesis testing unreliable.

These trade across provinces will affect the supply conditions across provinces, thus affecting the farm gate price. To assess the validity of no spatial correlation assumption, we estimate

$$\log(P_{imy}) = \beta_0 + \rho_1 W * \log(P_{imy}) + a_i + \delta M_y + \epsilon_{imy} \tag{4.7}$$

where W is the spatial weighting matrix (Darmofal, 2015). The values in the matrix represent the spatial relationships between provinces. If we find that ρ_1 is significant, then there is spatial correlation due to cross-province trade in our data. The results in section 4.6.1 indicate that ρ_1 is statistically insignificant. This may be the case because of two important reasons. First, there has been significant disintermediation in rice value chains in our study areas. Disintermediation refers to when one or more segments of the value chains are cut out (Reardon et al., 2014). In our case, millers are increasingly getting around traditional middlemen such as village traders and are buying directly from farmers. For example, the percentage of paddy volume sold to traders by farmers in our study region is only 9.5% in 2018 (Office of Agricultural Economics., 2019). As traders play a significant role in trade across provinces, the reduction in their role may decrease spatial correlation. Second, all provinces in our sample are located within one region (Northeast Thailand), and this region has a surplus of paddy supply. Hence, if there is cross-province trade, this trade is likely to occur between provinces across regions, rather than between provinces within our study region. Since paddy trade across provinces in our study region is likely to be minimal, there is no spatial correlation in our data. In sum, we believe that the assumption of no spatial correlation because of cross-province trade is reasonable in our setting.

Given that 4-year and 5-year lagged OFS are valid IVs, we estimate

$$\Delta \log(P_{imy}) = \beta_2 + \phi_1 \Delta \widehat{OFS_{iy}} + \delta M_y + \Delta \epsilon_{imy} \tag{4.8}$$

$$\Delta Pvol_{iy} = \beta_3 + \phi_2 \Delta \widehat{OFS_{iy}} + \delta M_y + \Delta \mu_{iy} \tag{4.9}$$

where $\Delta \widehat{OFS_{iy}}$ is the predicted value of ΔOFS_{iy} obtained from the following first-stage regression.

$$\Delta OFS_{iy} = \alpha_{y-4} OFS_{i,y-4} + \alpha_{y-5} OFS_{i,y-5} + \delta M_y + \Delta \varepsilon_{iy} \tag{4.10}$$

4.5 Data and descriptive statistics

Figure 4.4 depicts our study areas. Thailand is divided into four regions, and all provinces in our samples are in the Northeast region. This region is the major rice-producing region, with annual paddy production of 11.02 million tons, accounting for 45.5% of total paddy production in Thailand (Suebpongsang et al., 2020).

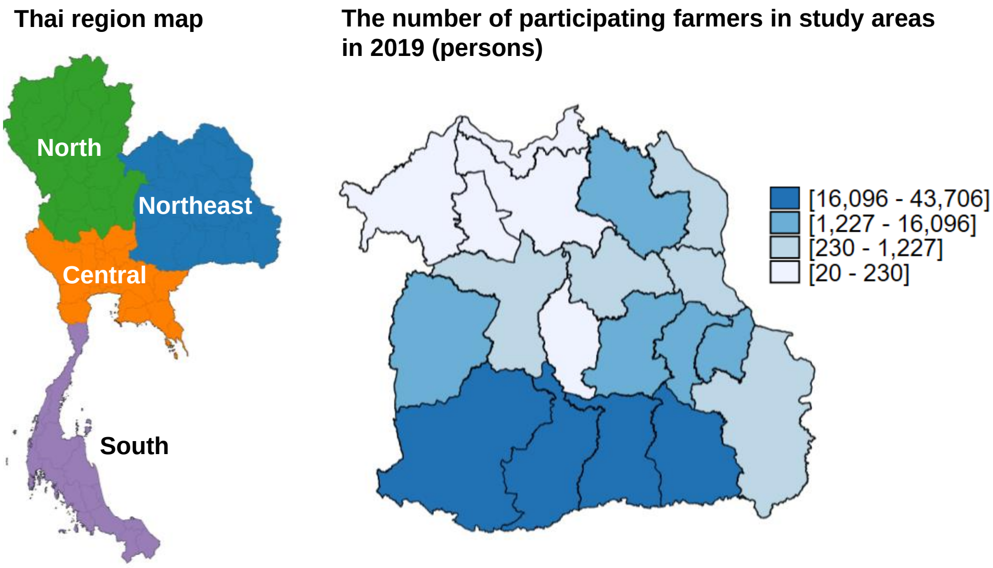


Figure 4.4: *left,* the map of Thailand; *right*, the number of participating farmers in our study areas

The on-farm storage intervention was implemented by the bank (BAAC) across the Northeast region. The loan was offered to farmers who grow Jasmine rice variety, non-glutinous rice variety, and glutinous rice variety. Here, we utilize only Jasmine rice variety data because the majority of farmers who participated in the intervention grow Jasmine rice. For example, in 2019, 69% of farmers who took up the loan grew Jasmine rice. Moreover, Jasmine rice's market price data are more available (in terms of locations and time) than other rice varieties. Figure 4.4 *(right)* shows that the number of Jasmine rice farmers who took up the harvest loan varies across provinces. In 2019, 174,289 Jasmine rice farmers took up the loan.

The data used in this article contain 19 provincial-level observations in Northeast Thailand, running from the marketing year 2001/02-2018/19, and come from serval sources. The data are aggregated or averaged by provinces. The aggregate on-farm storage quantity under on-farm storage intervention data are from the Bank for Agriculture and Agricultural Cooperatives and The Department of Internal Trade, The Ministry of Commerce. The average farm gate prices of Jasmine paddy are from the Agricultural Data Operation Center by The Office of Agricultural Economics, The Ministry of Agriculture and Cooperatives. The average rainfall data are from Climatic Data Service Center by the Thai Meteorological Department, The Ministry of Digital Economy and Society. To conduct placebo analyses (Athey and Imbens, 2017), we use the retail price of Koshihikari rice in Japan as pseudo outcomes. Koshihikari retail rice price data are from the Statistics Bureau of Japan. The farm gate price variables were deflated using the consumer price index with the base year 2015 from The Bureau of Trade and Economic Indices. Koshihikari retail rice price variables also were deflated using the consumer price index with the base year 2015 from the Statistics Bureau of Japan. Table 4.1 reports the descriptive statistics for our sample.

Table 4.1: Summary statistics

Variables	Mean	Std. dev.	Unit
Dependent variables			
Jasmine paddy			
Farm gate price at October	11,334.23	3,623.69	Baht per ton
Farm gate price at November	10,905.00	3,505.86	Baht per ton
Farm gate price at December	10,983.91	3,492.60	Baht per ton
Farm gate price at January	11,247.23	3,447.38	Baht per ton
Farm gate price at February	11,500.45	3,440.38	Baht per ton
Farm gate price at March	11,597.77	3,325.22	Baht per ton
Farm gate price at April	11,800.38	3,438.70	Baht per ton
Farm gate price at May	11,826.57	3,448.26	Baht per ton
Farm gate price at June	11,722.13	3,286.97	Baht per ton
Farm gate price at July	11,827.86	3,216.05	Baht per ton
Farm gate price at August	11,953.71	3,242.53	Baht per ton
Farm gate price at September	12,068.36	3,274.62	Baht per ton
Farm gate price volatility	0.07	0.05	-
Koshihikari rice			
Retail price at October	2,400.41	272.93	Yen per 5 kilograms
Retail price at November	2,408.92	289.71	Yen per 5 kilograms
Retail price at December	2,406.90	297.92	Yen per 5 kilograms
Retail price at January	2,409.01	312.78	Yen per 5 kilograms
Retail price at February	2,403.91	314.03	Yen per 5 kilograms
Retail price at March	2,400.29	294.48	Yen per 5 kilograms
Retail price at April	2,396.49	270.79	Yen per 5 kilograms
Retail price at May	2,393.03	264.63	Yen per 5 kilograms
Retail price at June	2,387.14	259.62	Yen per 5 kilograms
Retail price at July	2,388.92	263.78	Yen per 5 kilograms
Retail price at August	2,386.55	261.93	Yen per 5 kilograms
Retail price at September	2,385.01	260.07	Yen per 5 kilograms
Retail price volatility	0.02	0.02	
Independent variables			
On-farm storage quantity	1.16	2.54	20,000 tons
Rain at September	283.24	139.17	Millimeter per month
Observations	342		

4.6 Results and supplementary analyses

4.6.1 Testing instrument relevance and spatial correlation

Table 4.2 shows the estimations of first-stage regression (Equation 4.10) using ordinary least squares (OLS) regression to illustrate the relevance of our instrumental variables. In the last row, we report the F-statistic for joint significance. This is because there is a substantial correlation between the lags of the on-farm storage quantity, and this multicollinearity makes it challenging to estimate the effect at each lag precisely. Based on the F-statistics, the fourth lag and the fifth lag of the on-farm storage quantity are jointly significant, even though the fifth lag is insignificant. Thus, our results confirm that the differenced on-farm storage quantity under the intervention is highly correlated with 4-year and 5-year lagged on-farm storage quantity.

Table 4.2: First-stage regressions and instrument relevance

Dependent variable: ΔOFS_{iy}	
	OLS
Independent variables	
$OFS_{i,y-4}$, fourth lag	-0.2419***
	[0.0511]
$OFS_{i,y-5}$, fifth lag	0.0213
	[0.0340]
constant	-2.2825***
	[0.4911]
Adjusted R-squared	0.296
Observations	247
F-test of the overall significance (p-value)	0.000

Note: because observations for which lagged observations are unavailable are dropped, our sample size becomes smaller. The figures in brackets below the estimates are the robust standard errors, clustered by provinces. To save space, controls for year fixed effects are not shown. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

In Table 4.3, we perform a test to support the validity of no spatial correlation assumption by estimating Equation 4.7. In column (1), we report the estimated coefficient of the "spatially lagged dependent variable" variable. We find no significant association between the farm gate price in one province and the nearby provinces' farm gate price. Therefore, there is no spatial correlation due to cross-province trade in our data.

Table 4.3: Testing the spatial correlation

	Coefficient on spatially lagged dependent variable ($W * \log(P_{imy})$)		
	OLS (1)	Pseudo R-squared (2)	Observations (3)
Dependent variable			
Panel A: harvesting period			
Log (P_{i10y})	0.00003	0.973	342
	[0.00107]		
Log (P_{i11y})	-0.00150	0.956	342
	[0.00136]		
Log (P_{i12y})	-0.00068	0.968	342
	[0.00122]		
Panel B: Non-harvesting period			
Log (P_{i1y})	0.00116	0.969	342
	[0.00133]		
Log (P_{i2y})	0.00086	0.974	342
	[0.00130]		
Log (P_{i3y})	0.00040	0.978	342
	[0.00119]		
Log (P_{i4y})	-0.00026	0.978	342
	[0.00099]		
Log (P_{i5y})	0.00018	0.981	342
	[0.00097]		
Log (P_{i6y})	0.00043	0.974	342
	[0.00090]		
Log (P_{i7y})	-0.00037	0.959	342
	[0.00113]		
Log (P_{i8y})	0.00012	0.959	342
	[0.00107]		
Log (P_{i9y})	0.00003	0.958	342
	[0.00114]		

Note: The figures in brackets below the estimates are the standard errors. All regressions also include year fixed effects. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

4.6.2 Effects of on-farm storage intervention on local farm gate prices

Table 4.4 presents the estimation results of the effect of the change in local supply caused by on-farm storage intervention on the farm gate price at the main harvesting month (November). We begin with a simple analysis. In column (1), we simply regress the differenced log farm gate price in November on the differenced on-farm storage quantity under the intervention. This simple regression analysis indicates that the increase in on-farm storage quantity under the intervention or the decrease in local supply in the markets caused the farm gate price in November to decrease. This result contradicts the theoretical prediction that the decrease in local supply due to the intervention will increase the farm gate prices. This contradicted result is expected because column (1) fails to control the endogeneity problem, leading to bias estimation. In particular, this result may be driven by reverse causality. That is, the decrease in the farm gate prices leads to the increase in the on-farm storage quantity or the decrease in local supply in the markets because when the farm gate prices are low, farmers are more likely to participate in the intervention.

Table 4.4: OLS and 2SLS estimates of the effects of the change in local supply caused by on-farm storage intervention on the farm gate prices at the main harvesting month

	Dependent variable: Δlog (the farm gate price in November, P_{i11y})	
Estimation methods	OLS (1)	2SLS (2)
Independent variables		
1. Δon-farm storage quantity under the intervention (ΔOFS_{iy})	-0.0194** [0.0069]	0.0131** [0.0055]
2. Observations	323	247
3. Adjusted R-squared	0.035	0.896
4. First stage F-statistic		33.781
5. Sargan test of overidentifying restrictions (*p-value*)		0.132
6. First-order serial correlation test (*p-value*) or AR1 test		0.019
7. Second-order serial correlation test (*p-value*) or AR2 test		0.051
8. *p-value* ΔOFS_{iy}		0.017
9. *p-value* ΔOFS_{iy} bootstrap		0.080

Note: The figures in brackets below the estimates are the robust standard errors, clustered by provinces. To check robustness to small cluster standard error adjustments, *p-value* from the standard specification is compared to *p-values* drawn from the wild bootstrap procedure proposed by Cameron et al. (2008). To save space, in column (2), controls for year fixed effects are not shown. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

Column (2) attempts to estimate the causal effect of the change in local supply caused by the intervention on the farm gate prices in November. We tackle reverse causality and other sources of endogeneity by using the instrumental variable method. Namely, we apply the two-stage least square (2SLS) procedure to estimate Equation 4.8 using 4-year and 5-year lagged on-farm storage quantity as IVs. As we use lags of storage quantity as IVs, our estimates require that the error term in Equation 4.3 be serially uncorrelated. This assumption is testable. Specifically, if the error term is serially uncorrelated, we will reject the null of no serial correlation at order 1 but not at order 2 (Arellano and Bond, 1991; Roodman, 2009). As shown in the sixth and seventh rows in column (2), the test for first-order serial correlation rejects the null of no-first serial correlation. However, it fails to reject the null of no second-order serial correlation. Therefore, there is no serial correlation in the error term, as desired. We can also test whether our instruments are uncorrelated with the error term (exclusion restriction assumption) because we have more than one instrument. The *p-value* of the Sargan test (fifth row) indicates that we fail to reject the null hypothesis that all IVs are uncorrelated with the error. Thus, the fourth and fifth lags of on-farm storage quantity are valid instruments. In the fourth row, we report the F-statistic for the first-stage regression for the differenced on-farm storage quantity. The instrument appears sufficiently strong to avoid bias caused by weak instruments. As shown in the first row, the IV estimates turn the effect of the intervention from negative to positive. The coefficient on the on-farm storage quantity is now positive and statistically significant at the 5% level. This implies that an increase in the on-farm storage quantity under the intervention by 20,000 tons, which is equal to 20,000 tons decrease in local supply in the markets (around 6.24% of average production in study areas), causes the farm gate price in November to increase 1.31%. As we have a small number of clusters (we have 19 clusters), one might be concerned about the reliability of statistical inference. Cameron et al. (2008) show that cluster-robust standard error is downward biased with a small number of clusters. Thus, we check our results' robustness by drawing a *p-value* from the wild bootstrap procedure proposed by Cameron et al. (2008). In the ninth row, we show the *p-value* from this procedure, and the eighth row show *p-value* from the standard procedure. Although we do see some decrease in statistical precision, this adjustment is small. Hence, a small number of clusters is not a substantial concern in our analysis.

Table 4.5 shows the estimation results of the effect of the change in the local supply caused by the intervention on the farm gate price each month. Column (1) in Table 4.5 has the same empirical specification as in column (2) in Table 4.4, except that we replace the dependent variable with the farm gate prices from other months. In column (1), we report the estimated coefficient of the "the differenced on-farm storage quantity" variable. Columns (2) to (4) report three diagnostics for consistent estimation. Columns (6) and (7) report the *p-value* of the "the differenced on-farm storage quantity" variable drawn from the standard procedure and the wild bootstrap procedure, respectively. Panel H reports the effect of the intervention on the farm gate prices during the harvesting period. We find that only the estimated results for November are reliable in the harvesting period. The results in October and December are unreliable because the serial correlation diagnostics in columns (3) and (4) are not satisfactory. This invalidates the use of the 4-year and 5-year lagged on-farm storage quantity as instruments.

Table 4.5: 2SLS estimates of the effects of the change in local supply caused by on-farm storage intervention on the local farm gate price in each month

	Coefficient on Δon-farm storage quantity under the intervention (ΔOFS_{iy})						
	2SLS (1)	Over. test (2)	AR1 test (3)	AR2 test (4)	Adj. R-squared (5)	*p-value* ΔOFS_{iy} (6)	*p-value* ΔOFS_{iy} bootstrap (7)
Dependent variables							
Panel H: harvesting period							
ΔLog (P_{i10y})	-0.0004	0.039	0.005	0.025	0.896	0.933	0.949
	[0.0050]						
ΔLog (P_{i11y})	0.0131**	0.132	0.019	0.051	0.896	0.017	0.080
	[0.0055]						
ΔLog (P_{i12y})	0.0114*	0.605	0.012	0.002	0.898	0.082	0.391
	[0.0066]						
Panel N: Non-harvesting period							
ΔLog (P_{i1y})	0.0067	0.255	0.027	0.025	0.899	0.188	0.472
	[0.0051]						
ΔLog (P_{i2y})	0.0085***	0.822	0.010	0.589	0.925	0.006	0.058
	[0.0031]						
ΔLog (P_{i3y})	0.0054*	0.344	0.002	0.436	0.954	0.052	0.028
	[0.0028]						
ΔLog (P_{i4y})	0.0116***	0.106	0.001	0.154	0.960	0.000	0.025
	[0.0032]						
ΔLog (P_{i5y})	0.0086***	0.273	0.001	0.005	0.969	0.000	0.022
	[0.0022]						
ΔLog (P_{i6y})	0.0136***	0.039	0.000	0.002	0.941	0.004	0.079
	[0.0047]						
ΔLog (P_{i7y})	0.0164***	0.023	0.002	0.008	0.909	0.005	0.027
	[0.0058]						
ΔLog (P_{i8y})	0.0115***	0.027	0.000	0.116	0.901	0.004	0.022
	[0.0039]						
ΔLog (P_{i9y})	0.0083**	0.074	0.001	0.567	0.858	0.015	0.071
	[0.0034]						

Note: The figures in brackets below the estimates are the robust standard errors, clustered by provinces. To save space, controls for year fixed effects are not shown. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

Panel N reports the effect of the change in local supply caused by on-farm storage intervention on the farm gate prices during the non-harvesting period. Column (2) to (4) indicates that all the diagnostics for the unbiased estimation of the effect of the intervention on the farm gate price in February, March, April, and September are satisfactory. We find that the decrease in local supply caused by the intervention has a positive and statistically significant effect on the farm gate prices in February, March, April, and September. Namely, an increase in the on-farm storage quantity under the intervention by 20,000 tons causes the farm gate price in February, March, April, and September to increase by 0.85%, 0.54%, 1.16%, and 0.83%, respectively. These results imply that many participating farmers did not repay the loan by forfeiting their paddy to the state-owned bank (BAAC). On the other hand, the estimated results for January, May, June, July, and August are unreliable because three diagnostics in columns (2) to (4) are not satisfactory.

4.6.3 Effects of on-farm storage intervention on the farm gate price volatility

Table 4.6 presents the estimation results of the effect of the change in local supply caused by on-farm storage intervention on the farm gate price volatility. In column (1), we simply regress the differenced farm gate price volatility on the differenced on-farm storage quantity under the intervention. This simple regression analysis indicates that on-farm storage quantity under the intervention is negatively associated with the farm gate price volatility. The coefficient on the on-farm storage quantity indicates that an increase in the on-farm storage quantity by 20,000 tons is associated with 0.08% decrease in the farm gate price volatility. As column (1) does not address all sources of endogeneity problem, the OLS regression in this column is bias and unlikely to have a causal interpretation. Column (2) controls all sources of endogeneity by using the instrumental variable method. In the fourth row, we report the F-statistic for the first-stage regression for the differenced on-farm storage quantity. The instrument appears sufficiently strong to avoid bias caused by weak instruments. All the diagnostics in the fifth to seventh rows are also satisfactory for consistent estimation. As shown in the first row in column (2), the coefficient on the on-farm storage quantity remains negative but turns statistically insignificant. Therefore, we conclude that the change in local paddy supply caused by the intervention in our setting cannot stabilize the farm gate price inter-seasonally.

Table 4.6: OLS and 2SLS estimates of the effects of the change in local supply caused by on-farm storage intervention on rice price volatility

Dependent variable: Δfarm gate price volatility (the coefficient of variation, $\Delta Pvol_{iy}$)		
Estimation methods	OLS (1)	2SLS (2)
Independent variables		
1. Δon-farm storage quantity under the intervention (ΔOFS_{iy})	-0.0081***	-0.0024
	[0.0011]	[0.0021]
2. Observations	323	247
3. Adjusted R-squared	0.050	0.899
4. First stage F-statistic		33.78
5. Sargan test of overidentifying restrictions (*p-value*)		0.228
6. First-order serial correlation test (*p-value*) or AR1 test		0.002
7. Second-order serial correlation test (*p-value*) or AR2 test		0.073
8. *p-value* ΔOFS_{iy}		0.263
9. *p-value* ΔOFS_{iy} bootstrap		0.375

Note: The figures in brackets below the estimates are the robust standard errors, clustered by provinces. To save space, in column (2), controls for year fixed effects are not shown. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

4.6.4 Supplementary analyses

In this section, we seek to shed light on the credibility of our findings by conducting placebo analyses and robustness checks.

4.6.4.1 Placebo analyses

The basic idea of placebo analyses is to replicates the primary analysis with the outcome replace by a pseudo outcome that is known not to be affected by the variable of interest. Since the true value of the effect of the variable of interest on a pseudo outcome is zero, we must fail to reject the null hypothesis to be able to conclude that our findings are credible. In contrast, if the null hypothesis is rejected, we must conclude that our findings are not credible at all. This approach has been widely used in program evaluation (Athey and Imbens, 2017).

We use the retail price of Koshihikari rice in Japan as pseudo outcomes. Koshihikari rice retail prices are ideal pseudo outcomes because they are known not to be affected by on-farm storage intervention in the Thai Jasmine rice markets. This is the case because of two important reasons. First, Japan imports a tiny amount of Jasmine rice from Thailand. For example, in 2019, Japan imported only 3,000 tons of Jasmine rice from Thailand (Ministry of

Commerce, 2020). Second, for Japanese consumers, the possibility of substitution between Koshihikari rice and Jasmine rice is very low because Koshihikari rice is short grain rice, whereas Jasmine rice is long grain rice. Therefore, on-farm storage intervention in Thailand will not affect Koshihikari rice retail price in Japan. To match Japan and Thailand's data, we first randomly selected 19 prefectures from 21 prefectures in Tohoku, Kanto (except Tokyo), and Chubu regions in Japan. We then randomly matched (one-on-one) 19 prefectures in Japan with 19 provinces in Thailand.

Table 4.7 reports the results of placebo analyses. We estimate the same specifications as in Table 4.5, but with the retail price of Koshihikari rice and the volatility of Koshihikari rice retail prices as dependent variables. As expected, all the diagnostics in columns (2) to (4) for 13 dependent variables are satisfactory for consistent estimation. Column (1) shows that the on-farm storage quantity's coefficients are highly statistically insignificant for all 13 dependent variables. It means that the change in local supply induced by the intervention in Thailand does not affect the level and volatility of Koshihikari rice's retail price in Japan, as expected. The results of all 13 placebo tests in Table 4.7 indicate that the estimation results in Tables 4.5 and 4.6 are unlikely to be spurious. Therefore, we conclude that our findings in Tables 4.5 and 4.6 are credible.

Table 4.7: 2SLS estimates of the effects of the change in local supply caused by on-farm storage intervention in Thailand on retail rice price in Japan

	Coefficient on Δon-farm storage quantity under the intervention (ΔOFS_{iy})						
	2SLS (1)	Over. test (2)	AR1 test (3)	AR2 test (4)	Adj. R-squared (5)	*p-value* ΔOFS_{iy} (6)	*p-value* ΔOFS_{iy} bootstrap (7)
Dependent variables							
Rice Price level (observations = 247)							
Panel A: harvesting period							
ΔLog (P_{i10y})	-0.0014 [0.0049]	0.946	0.000	0.613	0.439	0.781	0.833
ΔLog (P_{i11y})	0.0017 [0.0043]	0.574	0.001	0.312	0.582	0.689	0.711
ΔLog (P_{i12y})	0.0035 [0.0057]	0.551	0.002	0.675	0.570	0.539	0.719
Panel B: Non-harvesting period							
ΔLog (P_{i1y})	-0.0014 [0.0045]	0.575	0.013	0.595	0.509	0.758	0.759
ΔLog (P_{i2y})	-0.0056 [0.0046]	0.235	0.003	0.290	0.496	0.225	0.213
ΔLog (P_{i3y})	-0.0023 [0.0052]	0.945	0.001	0.112	0.534	0.660	0.718
ΔLog (P_{i4y})	0.0026 [0.0057]	0.687	0.009	0.256	0.470	0.649	0.717
ΔLog (P_{i5y})	-0.0093 [0.0057]	0.133	0.005	0.331	0.444	0.100	0.047
ΔLog (P_{i6y})	-0.0057 [0.0060]	0.341	0.019	0.920	0.458	0.338	0.336
ΔLog (P_{i7y})	-0.0029 [0.0057]	0.912	0.007	0.420	0.568	0.610	0.613
ΔLog (P_{i8y})	-0.0006 [0.0097]	0.347	0.004	0.509	0.484	0.947	0.940
ΔLog (P_{i9y})	0.0049 [0.0079]	0.749	0.003	0.450	0.468	0.533	0.638
Rice price volatility (observations = 247)							
$\Delta Pvol_{iy}$	0.0004 [0.0012]	0.791	0.001	0.779	0.024	0.751	0.768

Note: The figures in brackets below the estimates are the robust standard errors, clustered by provinces. To save space, controls for year fixed effects are not shown. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

4.6.4.2 Robustness checks

In this section, we perform various robustness checks to demonstrate the robustness of our results. First, we check whether our results are robust to different ways of instrumenting. In our main specification, we use 4-year and 5-year lagged on-farm storage quantity ($OFS_{i,y-4}$, $OFS_{i,y-5}$) as IVs. However, we can also use the differenced on-farm storage quantity ($\Delta OFS_{i,y-3}$, $\Delta OFS_{i,y-4}$) as IVs. In Table 4.8, we replace $OFS_{i,y-4}$ and $OFS_{i,y-5}$ as instruments with $\Delta OFS_{i,y-3}$ and $\Delta OFS_{i,y-4}$. We find that the decrease in local supply caused by the intervention has a positive and significant effect on the farm gate prices in November, February, and April, and it has no significant effect on the farm gate price volatility. However, unlike in the main specification, we find the statistically insignificant effect of the intervention on the farm gate price in March and September. We also find that we could not precisely estimate the effect of the intervention on the farm gate prices in October, January, May, June, July, and August. These findings are very similar to the findings in Table 4.5. Therefore, our results are robust to alternative ways of instrumenting.

Second, in Appendix Table K1, we explore whether our results are robust to alternative estimation methods. The first column presents the results using a 2-stage least squares (2SLS) estimator, which is our main estimation method. Columns (2) and (3) uses 2-step GMM estimator and a limited-information maximum likelihood (LIML) estimator, respectively. Column (4) uses Fuller's (1977) modified LIML estimator with Fuller's alpha equal to 4. We find that, regardless of estimation methods, the results are similar both in terms of statistical significance and magnitude.

Third, we assess whether our results are robust to the inclusion of other explanatory variables. We estimate similar specifications as in Table 4.5, except that we now include rain in September as independent variable. Rain in September is expected to affect the flowering of Jasmine rice, thus affecting yield. Table K2 in the Appendix shows that these additional controls have little effect on our estimates.

Lastly, we check whether specific provinces affect the estimates. In Appendix Table K3, we estimate our preferred specification by excluding the top 2 provinces with the largest average amount of on-farm storage under the intervention per year during marketing year 2006/07 to 20018/19. Except in September, we find results that are very similar to our main results, establishing that specific provinces do not drive our findings.

Table 4.8: 2SLS estimates of the effects of on-farm storage intervention using different ways of instrumenting

	Coefficient on Δon-farm storage quantity under the intervention (ΔOFS_{iy})						
	2SLS (1)	Over. test (2)	AR1 test (3)	AR2 test (4)	Adj. R-squared (5)	*p-value* ΔOFS_{iy} (6)	*p-value* ΔOFS_{iy} bootstrap (7)
Dependent variables							
Rice Price level (observations = 247)							
Panel A: harvesting period							
ΔLog (P_{i10y})	0.0166*** [0.0044]	0.032	0.004	0.424	0.863	0.000	0.013
ΔLog (P_{i11y})	0.0249*** [0.0051]	0.051	0.021	0.244	0.869	0.000	0.005
ΔLog (P_{i12y})	0.0192** [0.0084]	0.388	0.010	0.002	0.883	0.022	0.140
Panel B: Non-harvesting period							
ΔLog (P_{i1y})	0.0087 [0.0068]	0.230	0.025	0.025	0.897	0.199	0.408
ΔLog (P_{i2y})	0.0062** [0.0029]	0.737	0.009	0.542	0.927	0.034	0.153
ΔLog (P_{i3y})	0.0024 [0.0024]	0.343	0.002	0.464	0.955	0.324	0.351
ΔLog (P_{i4y})	0.0070* [0.0040]	0.122	0.000	0.111	0.964	0.081	0.059
ΔLog (P_{i5y})	0.0073** [0.0033]	0.311	0.001	0.006	0.970	0.024	0.041
ΔLog (P_{i6y})	0.0075* [0.0044]	0.047	0.000	0.001	0.946	0.089	0.154
ΔLog (P_{i7y})	0.0059 [0.0053]	0.024	0.001	0.003	0.918	0.272	0.354
ΔLog (P_{i8y})	-0.0018 [0.0057]	0.021	0.000	0.138	0.904	0.749	0.779
ΔLog (P_{i9y})	0.0032 [0.0085]	0.101	0.001	0.563	0.864	0.705	0.733
Rice price volatility (observations = 247)							
$\Delta Pvol_{iy}$	-0.0031 [0.0024]	0.180	0.002	0.076	0.899	0.201	0.390

Note: The figures in brackets below the estimates are the robust standard errors, clustered by provinces. To save space, controls for year fixed effects are not shown. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

4.7 Discussion and implications for policy and evaluation

4.7.1 Welfare benefits of on-farm storage intervention due to its market-level effect

Table 4.9 shows the welfare benefits to nonparticipating farmers from on-farm storage intervention's market-level effect for the marketing year 2015/16 from selected provinces. This exercise should be interpreted as an illustration of how our findings can be used to estimate the welfare benefits to nonparticipating farmers, rather than the comprehensive welfare analysis of the intervention, which involves gains and losses in consumers[60] and producer welfare (well-being).

To evaluate the welfare benefits to nonparticipating farmers, the estimation of the amount of paddy that farmers sell during the harvesting season is required. We estimate the amount of paddy available for sales during the harvesting season by subtracting Jasmine paddy production by the amount of Jasmine paddy under the intervention, the amount of household consumption, and the amount of seed used. The amount of household consumption is estimated by multiplying the number of Jasmine rice farming households by household size and per capita rice consumption. The amount of seed used is calculated by multiplying the planted area by the seed rate used per unit of area. We calculate the welfare benefit by multiplying the farm gate price increase in November due to the intervention with the amount of paddy sold in November. We assume that nonparticipating farmers sell all paddy available for sales in November.

Column (1) in Table 4.9 shows the available supply for sales during the harvesting period. Column (3) shows the percentage of the farm gate prices increase due to the intervention,

[60] To determine the welfare effects of on-farm storage intervention on consumers, we must examine interrelationships among markets. That is, we need to investigate how the local supply shock (induced by the intervention) that raises the equilibrium price in input (paddy) markets affects the equilibrium price or consumer price in output (milled rice) markets. Given that our paper's primary goal is to investigate the effect of on-farm storage intervention in input markets where the intervention is implemented, we leave the issue of interrelated market effects for future research.

which we calculate by multiplying the coefficient of the differenced on-farm storage quantity in November (1.31) with on-farm storage quantity under the intervention in column (2). Column (4) presents the farm gate price increase due to the intervention, which we calculated by subtracting the observed farm gate price in November with the counterfactual farm gate price, which we calculated by dividing the observed farm gate price in November with (1+(column (3)/100)). Column (5) illustrates the welfare benefits to nonparticipating farmers from the market-level effect of on-farm storage intervention. For example, the local supply change caused by the intervention increases the farm gate price in November in Surin province by 7.46%, or approximately $24.24 per ton. If nonparticipating farmers in Surin sell all of their surplus paddy this month, the aggregate welfare benefits to nonparticipating farmers in Surin will be $19.32 million.

Table 4.9: Welfare benefits to nonparticipating farmers from the market-level effect of on-farm storage intervention for the marketing year 2015/16 from selected provinces

Provinces	Available supply for sale (tons)	On-farm storage quantity under the intervention (tons)	Price increase due to the intervention (%)	Price increase due to the intervention ($/ton)	Welfare benefits ($ million)
	(1)	(2)	(3)	(4)	(5)
Surin	796,992	113,959	7.46	24.24	19.32
Nakhonratch asima	507,151	96,677	6.33	21.16	10.73
Buriram	639,525	72,033	4.72	14.99	9.58
Sisaket	720,647	44,156	2.89	8.97	6.46
Roiet	590,108	38,987	2.55	8.70	5.14
Sakonnakhon	85,692	21,118	1.38	4.43	0.38
Chaiyaphum	158,073	15,251	1.00	3.47	0.55
Total					52.16

Note: The original values are computed in Thai Baht, but to facilitate interpretation they are converted into U.S. dollars at the fixed exchange rate of 35.29 baht per dollar.

4.7.2 Implications for policy and evaluation

Our results carry two crucial implications for evaluators and policymakers. First, the economic impact assessment of on-farm storage interventions needs to include its market-level effect. Our findings show that on-farm storage intervention affects the equilibrium price in local rice markets. These market-level effects will affect the welfare of consumers and producers. In particular, our estimation shows that the welfare benefits to farmers from the market-level effect of on-farm storage intervention are substantial. Therefore, the failure to consider the market-level effect will result in an inaccurate estimate of the impact of the on-farm storage intervention on societal welfare, leading to erroneous policy conclusions and recommendations. This implication is also applied to the evaluation of any technological or infrastructure investments such as grain drying systems (e.g., Nguyen-Van-Hung et al., 2019) and hermetic storage technologies (e.g., Baributsa and Njoroge, 2020) that will improve farmers' ability to store. For example, the evaluation of the economic benefits from mechanical drying investment should include the benefits to adopters and the benefits to non-adopters in the areas where investments occur.

Second, on-farm storage interventions, when delivered at scale, can be used as an effective tool to enhance the local farm gate prices during the price crisis. Generally, the farm gate prices of grains are lowest at harvest time when supplies are plentiful. Our results show that on-farm storage intervention at scale can prevent the falling local farm gate prices due to excess supply at harvest. This implication is essential for governments seeking to enhance incomes for smallholder farmers who have no choice but to sell their crops at harvest. However, the impact on consumers needs to be carefully considered when implementing the interventions.

4.8 Conclusions

Although on-farm storage interventions such as providing loans at harvest will affect local market supply conditions, little effort has gone into investigating its market-level effect. This lack of research is due to the difficulty in organizing large-scale experiments and in identifying causal effects from non-experimental settings. This paper assesses the market-level effect of large-scale on-farm storage intervention that allows farmers to delay the sale of their crops in the Thai rice markets. To the best of our knowledge, this study is the first to detect the market-level effects of on-farm storage interventions by taking advantage of panel data. To address the endogeneity problem from observational data, we employ two econometric strategies. We first convert our data to first difference. We then instrument the differenced on-farm storage quantity under the intervention (it represents the change in local supply caused by the intervention) using 4-year and 5-year lagged on-farm storage quantity. These instruments satisfy both relevance and exclusion restriction assumptions. Using 18-year panel data from 19 provinces in Thailand, we obtained empirical results that are credible and robust across various robustness checks.

Our results show that the decrease in local supply caused by on-farm storage intervention positively and significantly affects the local farm gate prices in the harvesting and non-harvesting period. For example, an increase in on-farm storage quantity under the intervention by 20,000 tons, which implies 6.24% local supply contraction, causes the farm gate price in November (the main harvesting month) and in April to increase 1.31% and 1.16%, respectively. On the other hand, we find that the local supply change caused by the intervention cannot stabilize the farm gate price inter-seasonally in our setting. More generally, our results show that on-farm storage interventions at scale drive up the equilibrium market prices and increase the possibility that public credit programs could raise aggregate welfare (Burke et al., 2018).

Our results carry two crucial implications for policymakers and evaluators. First, the evaluation of the economic impact of on-farm storage interventions or any investments that will improve farmers' ability to store needs to include its market-level effect. Second, on-farm storage interventions, when delivered at scale, can be used by policymakers as an effective tool to prevent the falling local farm gate prices due to excess supply at harvest.

This study's limitation is that, while the investigation focuses on on-farm storage intervention in the Thai rice markets, it is unclear whether similar results would hold in other settings. Thus, future research using data from other crops and countries is needed. Moreover, measuring the effects at the household level and assessing the impact on consumers is necessary in the future in order to enlarge our knowledge about the market-level effect of on-farm storage interventions when delivered at scale.

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Appendix

Table K1: The estimation of the effects of on-farm storage intervention using various estimation methods

	Coefficient on Δon-farm storage quantity under the intervention (ΔOFS_{iy})			
Estimation methods	2SLS	2-Step GMM	LIML	Fuller (4)-LIML
	(1)	(2)	(3)	(4)
Dependent variable				
Rice Price level (observations = 247)				
Panel A: harvesting period				
ΔLog (P_{i10y})	-0.0004	-0.0005	0.0006	-0.0004
	[0.0050]	[0.0050]	[0.0069]	[0.0050]
ΔLog (P_{i11y})	0.0131**	0.0140**	0.0138**	0.0109**
	[0.0055]	[0.0055]	[0.0058]	[0.0046]
ΔLog (P_{i12y})	0.0114*	0.0142***	0.0116*	0.0098*
	[0.0066]	[0.0038]	[0.0067]	[0.0051]
Panel B: Non-harvesting period				
ΔLog (P_{i1y})	0.0067	0.0093**	0.0069	0.0056
	[0.0051]	[0.0045]	[0.0052]	[0.0040]
ΔLog (P_{i2y})	0.0085***	0.0080***	0.0085***	0.0064**
	[0.0031]	[0.0025]	[0.0031]	[0.0026]
ΔLog (P_{i3y})	0.0054*	0.0036*	0.0055*	0.0043**
	[0.0028]	[0.0020]	[0.0029]	[0.0021]
ΔLog (P_{i4y})	0.0116***	0.0105***	0.0131***	0.0095***
	[0.0032]	[0.0031]	[0.0037]	[0.0027]
ΔLog (P_{i5y})	0.0086***	0.0078***	0.0088***	0.0072***
	[0.0022]	[0.0020]	[0.0023]	[0.0018]
ΔLog (P_{i6y})	0.0136***	0.0097**	0.0184**	0.0137***
	[0.0047]	[0.0043]	[0.0075]	[0.0047]
ΔLog (P_{i7y})	0.0164***	0.0147**	0.0243*	0.0177***
	[0.0058]	[0.0058]	[0.0126]	[0.0067]
ΔLog (P_{i8y})	0.0115***	0.0111***	0.0207	0.0138**
	[0.0039]	[0.0039]	[0.0130]	[0.0055]
ΔLog (P_{i9y})	0.0083**	0.0066**	0.0118**	0.0082**
	[0.0034]	[0.0033]	[0.0052]	[0.0034]
Rice price volatility (observations = 247)				
$\Delta Pvol_{iy}$	-0.0024	-0.0038**	-0.0025	-0.0024
	[0.0021]	[0.0018]	[0.0026]	[0.0019]

Note: The figures in brackets below the estimates are the robust standard errors. To save space, controls for year fixed effects are not shown. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

Table K2: 2SLS estimates of the effects of on-farm storage intervention using the alternative specification

	Coefficient on Δon-farm storage quantity under the intervention (ΔOFS_{iy})						
	2SLS (1)	Over. test (2)	AR1 test (3)	AR2 test (4)	Adj. R-squared (5)	*p-value* ΔOFS_{iy} (6)	*p-value* ΔOFS_{iy} bootstrap (7)
Dependent variables							
Rice Price level (observations = 247)							
Panel A: harvesting period							
ΔLog (P_{i10y})	-0.0013 [0.0051]	0.052	0.004	0.020	0.897	0.803	0.829
ΔLog (P_{i11y})	0.0126** [0.0055]	0.176	0.021	0.063	0.897	0.022	0.093
ΔLog (P_{i12y})	0.0111 [0.0068]	0.638	0.014	0.003	0.898	0.100	0.430
Panel B: Non-harvesting period							
ΔLog (P_{i1y})	0.0062 [0.0052]	0.335	0.029	0.021	0.900	0.229	0.486
ΔLog (P_{i2y})	0.0085*** [0.0032]	0.815	0.011	0.591	0.924	0.007	0.062
ΔLog (P_{i3y})	0.0054* [0.0030]	0.319	0.002	0.454	0.954	0.068	0.040
ΔLog (P_{i4y})	0.0119*** [0.0033]	0.114	0.000	0.162	0.960	0.000	0.025
ΔLog (P_{i5y})	0.0087*** [0.0022]	0.281	0.001	0.005	0.969	0.000	0.026
ΔLog (P_{i6y})	0.0144*** [0.0048]	0.051	0.000	0.003	0.941	0.003	0.074
ΔLog (P_{i7y})	0.0173*** [0.0059]	0.029	0.002	0.011	0.908	0.004	0.025
ΔLog (P_{i8y})	0.0123*** [0.0041]	0.029	0.000	0.133	0.899	0.003	0.022
ΔLog (P_{i9y})	0.0093** [0.0036]	0.081	0.000	0.512	0.858	0.011	0.071
Rice price volatility (observations = 247)							
$\Delta Pvol_{iy}$	-0.0022 [0.0022]	0.258	0.002	0.075	0.900	0.333	0.492

Note: First stage F-statistic equals 30.65. The figures in brackets below the estimates are the robust standard errors. To save space, controls for year fixed effects are not shown. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

Table K3: 2SLS estimates of the effects of on-farm storage intervention without Surin and Nakhonratchasima samples

	Coefficient on Δon-farm storage quantity under the intervention (ΔOFS_{iy})						
	2SLS (1)	Over. test (2)	AR1 test (3)	AR2 test (4)	Adj. R-squared (5)	*p-value* ΔOFS_{iy} (6)	*p-value* ΔOFS_{iy} bootstrap (7)
Dependent variables							
Rice Price level (observations = 221)							
Panel A: harvesting period							
ΔLog (P_{i10y})	0.0038 [0.0054]	0.097	0.009	0.080	0.8895	0.481	0.663
ΔLog (P_{i11y})	0.0132*** [0.0045]	0.191	0.013	0.110	0.8972	0.003	0.045
ΔLog (P_{i12y})	0.0074** [0.0033]	0.275	0.007	0.006	0.9035	0.026	0.043
Panel B: Non-harvesting period							
ΔLog (P_{i1y})	0.0032 [0.0025]	0.125	0.033	0.061	0.8946	0.269	0.212
ΔLog (P_{i2y})	0.0079*** [0.0025]	0.797	0.013	0.522	0.9241	0.002	0.052
ΔLog (P_{i3y})	0.0065*** [0.0020]	0.158	0.003	0.624	0.9542	0.001	0.037
ΔLog (P_{i4y})	0.0117*** [0.0031]	0.194	0.001	0.084	0.9633	0.000	0.041
ΔLog (P_{i5y})	0.0086*** [0.0021]	0.435	0.002	0.005	0.9700	0.000	0.018
ΔLog (P_{i6y})	0.0101* [0.0052]	0.096	0.000	0.002	0.9454	0.054	0.259
ΔLog (P_{i7y})	0.0100 [0.0065]	0.033	0.004	0.007	0.9190	0.126	0.141
ΔLog (P_{i8y})	0.0072 [0.0044]	0.037	0.001	0.203	0.9045	0.104	0.114
ΔLog (P_{i9y})	0.0042 [0.0036]	0.194	0.001	0.987	0.8559	0.244	0.269
Rice price volatility (observations = 221)							
$\Delta Pvol_{iy}$	-0.0037* [0.0020]	0.692	0.003	0.117	0.8933	0.073	0.278

Note: First stage F-statistic equals 85.52. The figures in brackets below the estimates are the robust standard errors. To save space, controls for year fixed effects are not shown. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

Chapter 5 General conclusion and avenues for further research

My doctoral research aims to deepen our understanding about the effect of policy interventions that aim to solve farmers' low-income problems on the functioning of agricultural markets. Specifically, I evaluate three agricultural policy interventions in Thailand, including price support policy, promoting farmer organizations, and supporting on-farm storage. These interventions have been implemented over a decade in many developing countries. This dissertation used data from several sources for empirical analysis. In chapter 2 and 4, I used provincial-level data collected from several government agencies. In contrast, in chapter 3, I used individual-level field survey data collected from two provinces in Northeast Thailand. In this section, I first summarize the results from the dissertations. I then discuss implications for policy and evaluation. Lastly, I discuss avenue for future research.

5.1 Summary of results

In chapter 2, I address two research questions. First, how much oligopsony power do processors or intermediaries in the Thai Jasmine rice market have and exercise over farmers? Second, what are the market and welfare effects of price support policy in the presence of oligopsony? To answer the first question, I develop a rice market model consisting of rice supply and demand equations based on the NEIO framework. To answer the second question, I develop an imperfect competition model to evaluate the welfare effects of the Paddy Pledging Program (PPP), a price support policy in Thailand. Using 15-year data, 15 provincial-level with 225 observations, I find that intermediaries in the Thai Jasmine rice market have oligopsony power. The estimates of oligopsony power parameter (1 = highest level of oligopsony power) range from -0.39 to 0.65. I also find that intermediaries exercise oligopsony power over farmers. The estimated oligopsony price distortion ranges from -33% to 55%.

Using the above-estimated parameters to simulate the Thai Jasmine rice market under the paddy pledging program, I find that the price support policy increases the farm gate price by 8.4% and reduces the consumer price by 6.35%. As a result, the program increases consumer surplus and farmer surplus by \$10.6 million and \$38.8 million, respectively. However, I find that the program is inefficient. It imposes a deadweight loss to society of about \$34.9 million per year. Nevertheless, the program can be efficient by setting an optimal support price where the government does not have to buy rice from farmers. Next, I consider the income redistribution effect of the program. The program is effective in income redistribution because every public dollar spent on the program returns \$1.10 in income redistribution. My findings challenge generally accepted "wisdom" regarding price support policy in agricultural markets. The perceived wisdom regarding this policy is that it benefits farmers, hurts consumers, and always imposes a deadweight loss on society. Therefore, the government should eliminate the price support policy. However, my findings show that the price support policy can benefit both farmers and consumers in an imperfect competition market and can be designed to increase social welfare.

In chapter 3, I test the hypothesis that nonparticipating farmers or farmers who sell rice to private intermediaries in the areas where there is direct competition between marketing cooperatives and private intermediaries (treated areas) are likely to receive a higher price than those who sell rice in other areas (comparison areas). To test this hypothesis, I use language spoken at home as an instrument. Using data from randomly selected 360 households from 36 villages in treated and comparison areas, I find that nonparticipating farmers in treated areas receive 10.9% higher prices from private intermediaries than those who sell rice in comparison areas. This finding provides support for the view that the presence of marketing cooperatives can significantly force private intermediaries to competitively raise prices paid to farmers. Therefore, promoting farmer organizations' role in the rice value chains can generate a spillover effect or indirect effect.

In chapter 4, I address two research questions. First, does the change in local supply caused by on-farm storage interventions affect equilibrium market prices? Second, is this change in supply able to stabilize price inter-seasonally? To answer these questions, I use 4-year and 5-year lagged on-farm storage quantity as instrumental variables. I find that an increase in the on-farm storage quantity under the intervention by 20,000 tons, which is equal to 20,000 tons decrease in local supply in the markets, causes the farm gate price in November, February, March, April, and September to increase by 1.31%, 0.85%, 0.54%, 1.16%, and 0.83%, respectively. Using these estimated values to calculate the welfare benefits, I find that nonparticipating farmers gain considerable welfare benefits from on-farm storage intervention. For example, the local supply change caused by the intervention increases the farm gate price in November in Surin province by 7.46% or approximately $24.24 per ton. If nonparticipating farmers in Surin sell all of their surplus paddy this month, the aggregate welfare benefits to nonparticipating farmers in Surin will be $19.32 million. In contrast, I find that the increase in on-farm storage quantity under the intervention does not significantly reduce price volatility. Overall, chapter 4 shows that allowing farmers to store grains by offering them the harvest-time cash loan can affect the equilibrium market price. Hence, supporting on-farm storage can increase farm gate prices.

5.2 Implications for policy and evaluation

My dissertation provides 3 crucial evidence and 7 policy implications for agri-food policy debates regarding the welfare effect of price support policy in the presence of market power, the role of farmer organizations in agricultural development and agricultural markets, and the welfare implications of on-farm storage interventions when delivered on a massive scale.

The findings in chapter 2 point out that the policy prescription to deregulate agricultural markets in developing countries must be undertaken with caution. In an agricultural market with oligopsony power, government policies can be warranted not only to mitigate market distortion but also to protect small farmers and consumers from the adverse effects of market power. In other words, my findings have highlighted the need for market interventions when the markets function poorly due to a low competition level. In particular, when there is a market failure, a price support policy can be designed to improve the market's efficiency and thereby increase farmers' income and lower consumer prices.

The finding in chapter 3 shows that strengthening the role of farmer organizations in agricultural markets can benefit not only members but also non-members. Four implications emerged from this finding. First, evaluating the inclusiveness of marketing cooperatives toward poor farmers should not be limited to sampling and analyzing participating farmers only. Second, prior studies that do not control for the spillover effect of marketing cooperatives may underestimate the benefits of marketing cooperatives. Third, the spillover effect needs to be incorporated in the future evaluation of the marketing cooperative's performance. Finally, policies aiming at enhancing the role of marketing cooperatives in rice value chains should be aware of and address the free-rider problem to ensure that social welfare is maximized

The results in chapter 4 show that supporting on-farm storage by allowing farmers to access credit during the harvesting time can increase the local market prices. Hence, the evaluation of the economic impact of on-farm storage interventions or any investments that will improve farmers' ability to store needs to include its market-level effect. Moreover, on-farm storage interventions, when delivered at scale, can be used by policymakers as an effective tool to prevent the falling local farm gate prices due to excess supply at harvest.

Overall, it is possible to raise farmers' income through existing interventions to some degree, and the impact assessments of these interventions need to include their spillover effects and market-level effects.

5.3 Avenues for further research

There are at least three avenues for further inquiry for deepening our understanding about the effect of policy interventions that aim to solve farmers' low-income problems on the functioning of agricultural markets. Firstly, we need more empirical evidence on the effects of policy intervention on consumers. In chapter 2, we show that government policies can increase consumers' benefits by reducing oligopolistic middlemen's rent. In chapter 3, we show that cooperative activities have the possibility to increase consumers' benefits by reducing oligopolistic buyers' rent. Overall, policies and cooperative activities can counter oligopsony and oligopoly, that is, they can increase farmers' prices and may decrease consumers' prices. Hence, it is crucial to generate more evidence on the impact of policy interventions on consumer welfare.

The second avenue for further research is to analyze policy intervention's impact in other vertically related markets. This is because the agricultural markets are interlinked in complex ways. Hence, the intervention in one market may affect other vertically related markets. As an illustration, consider a simple agricultural supply chain:

[Input providers] ➔ [Farmers] ➔ [Intermediaries] ➔ [Consumers]

where farmers buy inputs such as seeds from input providers and then sell their crops to intermediaries such as traders and processors. And then, intermediaries sell processed crops to consumers. In this supply chain, there are three vertically related markets: the market between input providers and farmers, the market between farmers and intermediaries, and the market between intermediaries and consumers. Although the policy interventions that I evaluate take place in the market between farmers and intermediaries, it can impact other vertically related markets as well. For example, the price support policy assessed in chapter 2 may also impact the market between input providers and farmers. Namely, the increase in the price received by farmers caused by the price support policy may lead to the rise in land lease fee or fertilizer prices. Hence, we should analyze the impact of policy intervention in both the market where the policy is implemented and other vertically related markets.

The third avenue for future research is to investigate how technology can be used to solve farmers' low-income problems. In particular, the widespread adoption of mobile phones and the internet in rural areas creates the potential for enhancing the competition in agricultural markets. Mobile phones and the internet can be used to enhance the functioning of agricultural markets in developing countries in several ways. First, farmers can use mobile phones to speak to multiple intermediaries to collect price information. This price information may allow farmers to engage in optimal trade or arbitrage. Namely, a price difference between markets should induce farmers to reallocate their goods to the market that offers the highest price. Second, private sectors and governments can use a mobile phone as a platform to deliver market information to farmers through various mobile technologies such as short messaging service (SMS). For example, a subscription SMS service can transmit market information to farmers' phones. Third, private sectors and governments can use the internet kiosk to deliver market information to farmers. Lastly, private sectors and governments can set up an electronic market where intermediaries and farmers connect over an electronic network. This electronic market is likely to increase market competition as it integrates geographically distant markets within a common platform. By bridging information gaps and connecting buyers with sellers, mobile phones and the internet are likely to enhance the functioning of agricultural markets in developing countries. Therefore, we should evaluate the impact of mobile phones and the internet on the price received by farmers.