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

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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 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.

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 (Bizikova et al., 2020; 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 role 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., 2008; Hanisch et al., 2013; Jardine et al., 2014; Liang and Hendrikse, 2016; Sexton, 1990; Milford, 2012). 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

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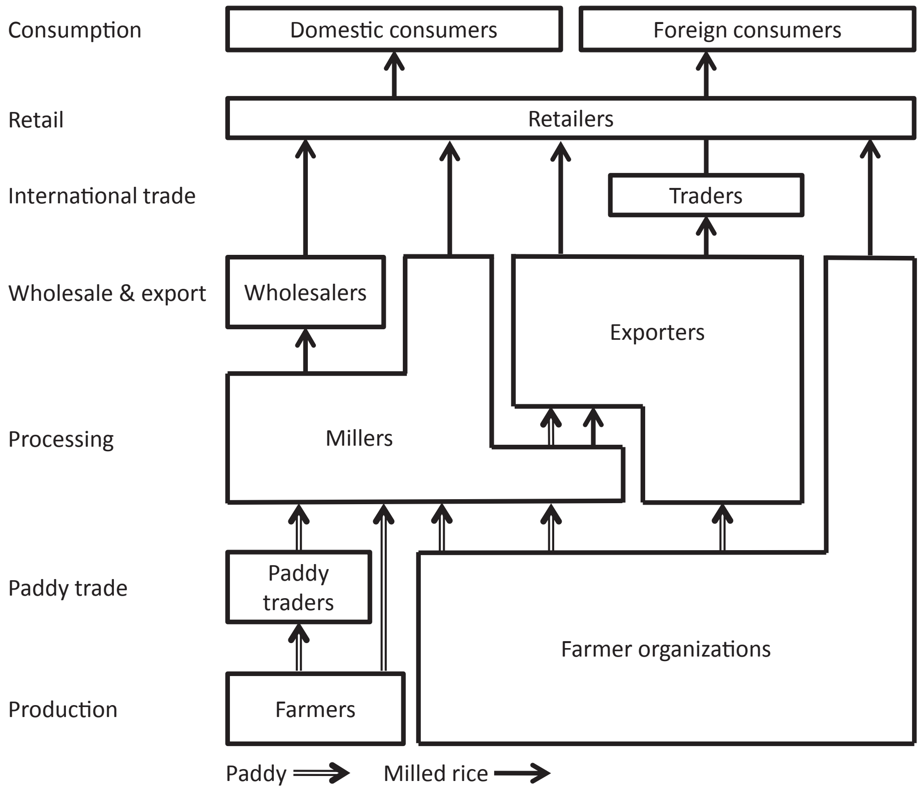

Fig. 1. Jasmine rice value chain in Thailand.

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 may not be able to 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' reception of 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 on estimating the effect of cooperatives on members or participating farmers only (Bachke, 2019; Barham and Chitemi, 2009; Bernard et al., 2008; 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[1] for the spillover effect of marketing cooperatives

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

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 policy implications. The last section concludes.

2. Background

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 ha 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. Fig. 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 Fig. 1 by expanding their operations into paddy trading, processing, and wholesale[2].

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[3] (National Statistical Office of Thailand, 2019). 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. Panel 1.1 in Table 1 shows the source of household income in Sisaket and Buriram. In 2017, the largest source of household income in Sisaket was rice farming (26.1%), followed by remittances from relatives (20.6%) and government assistance (15.5%). In Buriram, remittances from relatives were the largest source (19.5%) of household income, followed by rice farming (17.9%) and other farming activities (17.9%). Panel 1.2 in Table 1 shows the macro-provincial level characteristics of Sisaket and Buriram. These provinces have many similar macro characteristics[4] such as per capita income, 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 A1 in the Appendix shows that 92% of the investment in post-harvest technologies in two areas used outside funding

Table 1
Source of household income and macro-provincial level characteristics.

	Unit	Year	Sisaket	Buriram
Panel 1.1: Source of household income (100%)				
Rice farming	Percentage	2017	26.06	17.97
Remittances from relatives	Percentage	2017	20.61	19.50
Government assistance	Percentage	2017	15.54	11.62
Wages	Percentage	2017	11.70	10.18
Salaries	Percentage	2017	7.46	5.51
Other farming activities	Percentage	2017	13.04	17.98
Other	Percentage	2017	5.60	17.24
Panel 1.2 Macro-provincial level characteristics				
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 based on data from the 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), National Statistical Office of Thailand (2015), and Townsend (2017).

[2] 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.

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

[4] 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, and the level of public good provision between the two areas.

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 1) led farmer organizations to adopt different practices to participate in the Jasmine rice value chain (Fig. 1) when the Thai government implemented an interest-rate subsidy program for working capital loans for farmer organizations[5] 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[6], the agricultural marketing cooperative formed and operated by the clients of the Bank for Agriculture and Agricultural Cooperatives (BAAC)[7] in Sisaket or Sisaket Marketing Cooperative (SMC)[8] competed with private intermediaries to buy paddy from farmers in some areas within Sisaket.

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. 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 Fig. 2.

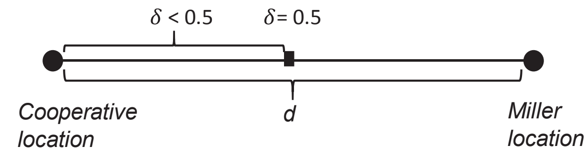

Fig. 2. Spatial rice market.

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. Similarly to Fafchamps and Hill (2005) who analyze farmers' decision whether to sell at the farm gate or to travel to the nearest market, we postulate that the farmer chooses to sell to the cooperative if

$$P^{m} - c^{m} < P^{co} - c^{co} \tag{1}$$

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 sells paddy to millers or milled rice to retailers (Fig. 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

$$P^{m} - (1-\delta)d < P^{co} - \delta d \tag{2}$$

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 its 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 (2), we have $\delta < 0.5 + 0.5b/d$. 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 behavior in order to retain some paddy suppliers. Let ω denote the level by which the miller increases the buying price. We have

$$\delta < 0.5 + 0.5(b-\omega)/d \tag{3}$$

Equation (3) shows that if the miller wants to retain half of its paddy suppliers, $\delta < 0.5$, it must set its 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 its price at a higher level than the price offered by the cooperative ($\omega = b + 0.5d$). Therefore, the presence of the marketing cooperative is likely to force the miller to raise prices paid to farmers.

Equation (3) also indicates that the magnitude of ω or the spillover effect of the presence of the marketing cooperative[9] depends 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 that can affect the magnitude of the spillover

[5] Under this program, farmer organizations can borrow money from the 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.

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

[7] BAAC, the largest rural development bank in Thailand, has intervened in agricultural value chains since 1989 by encouraging its clients to form marketing cooperatives.

[8] 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.

[9] 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" (Cotterill, 1997; Liang and Hendrikse, 2016; Royer, 2014; Sexton, 1990).

effect. Given that we focus on the role of marketing cooperatives, we discuss only the factors that may affect the level of the price premium.

At least three factors could affect the price premium. The first factor consists of the cooperative objectives. The cooperative may operate under different objectives, other than maximizing profit. For example, the cooperative may aim to maximize member returns or net price. Royer (2014) shows that the price offered by the cooperative depends on its 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[10] problems (Richards et al., 1998). These problems arise because the agents' (managers) actions, such as work-effort, are not directly observable by the principals (cooperative members). As a result, the agents may not act in the best interests of the principals. Hence, the contract design that will align the manager's personal objectives with those of the cooperative will likely affect the price premium offered by the cooperative to its members.

4. Empirical framework

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 the price received by farmers in each location is given by

$$\log(P_{ij}) = \beta_0 + \beta_1 T_i + \beta S_i^o + \beta S_i^u + \beta F_i^o + \beta F_i^u + \beta A_{ij}^o + \beta A_{ij}^u + \varepsilon_{1ij} \tag{4}$$

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 sales 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 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, andA_{ij}^u are unobserved, we instead estimate the model

$$\log(P_{ij}) = \beta_0 + \beta_1 T_i + \beta S_i^o + \beta F_i^o + \beta A_{ij}^o + \varepsilon_{2ij} \tag{5}$$

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, the regression is prone to 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^oor we could leave S_i^o, A_{ij}^o, and F_i^o out of Equation (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

$$\log(P_{ij}) = \beta_0 + \beta_1 T_i + \varepsilon_{3ij} \tag{6}$$

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.

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[11] 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 home? If yes, what is this language?". L_i equals one if the farmer speaks Lao Isan at home and zero

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

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

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.

4.2.1. 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[12], 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 sell their crops (e.g., Ruhinduka et al., 2020). However, we believe that culture variables no longer affect farm management in our case because agricultural 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 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 (Custodio et al., 2016, 2019) have driven intermediaries such as millers to conduct their market transactions based on quality standards[13] (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 lineages on market transaction outcomes.

Moreover, Table 5 panel D (section 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 their relevance to farm management that they 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[14] in our study areas (Keyes, 1967). In fact, social scientists have difficulties classifying cultural groups because individuals differ in skin color, language, the origin of birth, and religion, but it is unclear what dimension one should use. For example, in some countries, language is the key dividing line; in others, 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 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 relevance for agricultural production and markets. 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 price only through the competition between marketing cooperatives and private intermediaries, we must find no correlation between language and price when there is no competition (pretreatment period). However, if we find a correlation, it implies that Lao Isan language has some relevance to agricultural production and markets. To assess the correlation between language and price, we estimate

$$\log(P_{it}) = \alpha_5 + \alpha_6 L_i + \pi_t year_t + \mu_{it} \tag{7}$$

where P_{it} is the price received by farmer i in pretreatment year t; L_i is language spoken at home (1 = Lao Isan); $year_t$ represents year dummy variables; and μ_{it} is an error term. Using unbalanced panel data from the Townsend Thai Project (Townsend, 2017), 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 6.1). This finding implies that culture variables are not associated with prices in our setting. It also implies that although farmers maintain their traditional language, they 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.

4.2.2. 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 students' 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 be canceled out. Therefore, the language spoken at home is unlikely to affect farmers' ability in our setting.

[12] 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).

[13] 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).

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

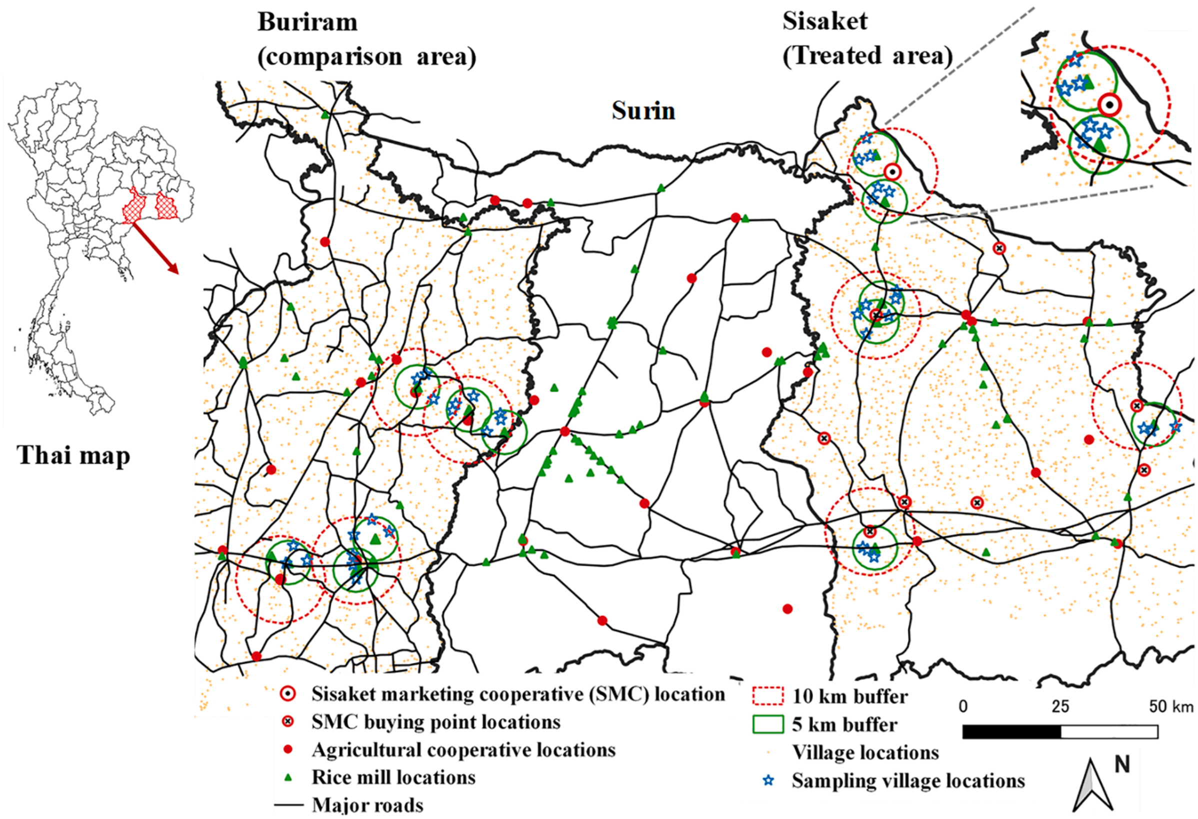

Fig. 3. Our study areas.

4.2.3. Language and the development of farmers' organizations

Despite being subjected to identical national institutions, the development of farmers' organizations in two areas results in 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 pointed out that cultures[15] 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 collectively act 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 were associated with cooperative size and the size were associated with the investment in drying technology, then all Lao Isan speaking provinces where Jasmine rice is grown would 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 account 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, which may increase trust between them. Moreover, it may be that the level of trust is not associated with language spoken at home. A study in the U.S. showed 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 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*):

$$Millca_n = \alpha_8 + \alpha_9 Size_n + \mu_n \tag{8}$$

where n indicates agricultural cooperatives and μ_n is an error term. The results in section 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 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.

4.2.4. Province fixed effect and price

Our analysis assumes that there is no price difference between Bur-

[15] 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).

Table 2
Summary statistics.

Variables	Unit	Selling locations Treated areas Mean	Std. dev.	Comparison areas Mean	Std. dev.
Paddy rice sales 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 members (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 include the language variable; we constructed this variable by using the village-level language data. If most of the villagers in the villages were found to speak Lao Isan at home, we assigned Lao Isan language to all households surveyed in this village.

iram 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[16] as all of our treatment samples are located within one province. To test the association between the province fixed effect and the price, we estimate

$$\log(P_{it}) = \pi_3 + \pi_4 S_i + \pi_t year_t + \mu_{it} \tag{9}$$

where S_i is a dummy variable (province fixed effect) equal to one if farmer i is in Sisaket and zero if he/she is 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 price (see section 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

$$\log(P_{ij}) = \beta_0 + \beta_1 \widehat{T}_i + \varepsilon_{4ij} \tag{10}$$

where $\widehat{T}_i$ (selling in treated area variable) 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 variables in equation (10), which satisfies

$$T_i = \alpha_0 + \alpha_1 L_i + \varepsilon_{5ij} \tag{11}$$

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.

5. Data and descriptive statistics

Fig. 3 depicts our study areas. To support the sampling design, we constructed a Geographic Information Systems (GIS) database for Sisaket and Buriram that includes road networks and the locations of agricultural cooperatives, rice millers, and villages. Road networks were obtained from the Minstry 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).

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 km 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 a 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

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

Table 3
Demographic characteristics of farmers by language spoken at home.

	Language spoken at home		
	Lao Isan (1)	Non-Lao Isan (2)	Difference (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.

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[17] related to the 2018/19 marketing year.

To support the validity of our IV, we use data from two sources. First, we use data from the Townsend Thai Monthly Survey[18], 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[19]. Second, we use data on cooperative rice milling capacity and cooperative size from Cooperative Promotion Department (2020a, 2020b). Table 2 reports the descriptive statistics.

6. Results and robustness checks

6.1. Instrumental variable's validity

Before presenting and discussing the 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 suggests that, except farm size, none of the demographic characteristics is significantly different from zero at the one percent level. Intuitively, these results make sense as one cannot choose the family in which one is born.

Next, to illustrate the relationship between the language spoken at home and the price received by farmers, Fig. 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 who received a price 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 received lower prices is relatively larger among Non-Lao Isan speaking than among Lao speaking farmers. For example, 64% of Non-Lao Isan speaking farmers received a price less than the average price of 13.2 baht per kilogram of paddy (red line), compared to only 38% of Lao Isan speaking farmers. 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 the treatment status.

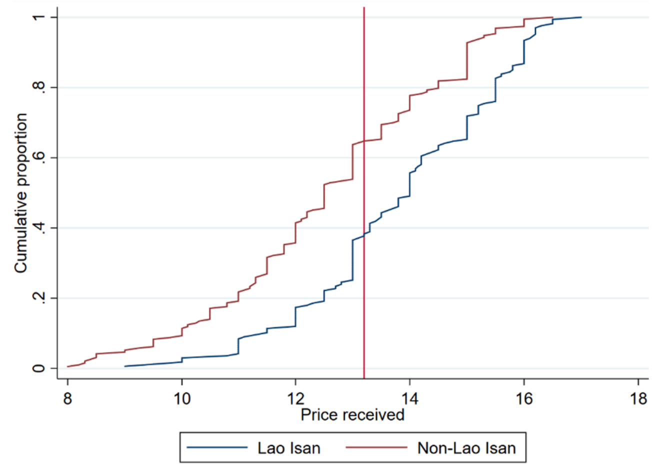

Fig. 4. Cumulative distribution functions of the price received by farmers, differentiated according to the language spoken at home.

Table 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 4, we examine the relationship between the language spoken at home and rice selling locations or treatment status. Different columns in Table 4 exhibit the estimations from several specifications of the first-stage IV regression (Equation (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.

In Table 5, we perform various tests to support the validity of the exclusion restriction assumption. In panels A, B, and C we estimate Equation (7), (8), and (9), respectively. In panel A, we find that Lao Isan language is unrelated to the price received by farmers during the pre-treatment period. Panel B indicates that there is no association between

[17] 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.

[18] For a more detailed description and information regarding the dataset, please refer to the Townsend Thai Project website at http://townsend-thai.mit.edu/data/monthly-surveys.shtml.

[19] The part of the sample after 2004 is dropped because no farmers from the sample in Buriram sold Jasmine rice to intermediaries between 2005 and 2014.

Table 5
Testing the validity of the exclusion restriction assumption.

Panel A: Dependent variable is paddy price received		Panel D: Dependent variable is Lao Isan	
Independent variables:	OLS	Independent variables:	OLS
		Farmers' marketing decisions	
Lao Isan (1 = Lao Isan)	−0.021	Selling wet paddy	−0.015
	[0.019]		[0.094]
Control for year	Yes	Selling to miller	0.012
R-squared	0.603		[0.121]
Observations	848	Selling months	−0.025
			[0.014]
Panel B: Dependent variable is milling capacity		*Local area characteristics*	
Independent variables:	OLS	Number of millers	0.109
			[0.143]
The size of agricultural cooperatives	0.043	Milling capacity	−0.000
	[0.074]		[0.000]
R-squared	0.001	*Farmer characteristics*	
Observations	147	Farm size	−0.007***
			[0.002]
Panel C: Dependent variable is paddy price received		Household size	0.009
Independent variables:	OLS		[0.019]
		Age	0.002
Sisaket (1 = Sisaket)	−0.022		[0.003]
	[0.016]	Male	−0.064
Control for year	Yes		[0.056]
R-squared	0.604	Education	0.010
Observations	848		[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.

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 (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 (Ba et al., 2019). Nevertheless, in our case, farm size is not correlated with the price (see Table 6). This may be the case because farm sizes in our study area are not large enough to increase farmers' bargaining power significantly. Nevertheless, even if farm size were correlated with the price, which in turn would cause our IV to affect the price indirectly, this indirect effect could be eliminated by including the farm size variable in Equation (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 6.3.2).

6.2. Results

We estimate Equations (5), (6) and (10), and present the results in Table 6, i.e. columns (1), (2), (3), respectively. Before discussing the estimation results pertaining to 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 6 reports the results of an OLS

Table 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]		
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.

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 sales, 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 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 squares (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.

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 the treatment status is statistically significant and indicates that nonparticipating farmers in treated areas receive a 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 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' and cooperatives' characteristics variables and the interaction term between these variables and the "selling in treated area" variable in Equation (10). Nevertheless, as discussed in section 4.1, these variables are endogenous. For example, farmers' characteristics 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 seriously bias the 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 female members 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 the price received by farmers, i.e., to estimate the average treatment effect, we leave the issue of spillover effect heterogeneity for future research.

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.

6.3.1. Controlling for observable heterogeneity

One may worry that our instrument is picking up nonmarketing cooperative-related differences in prices received across areas with 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 7 confirms that farmers in treatment and comparison areas 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 8).

Table 7
Comparison of variables between treated and comparison areas.

	Selling locations Treated areas (1)	Comparison areas (2)	Difference (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 8, we estimate the treatment effect for each sub-sample by using the same empirical specification as in Table 6, i.e., columns (1), (2), and (3) in Table 8 are the same as columns (1), (2), (3) in Table 6.

However, unlike in Table 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.

6.3.2. Relaxing the exclusion restriction assumption

The high 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 variables that could affect price. For example, a referee pointed out that the degree of group heterogeneity might influence bargaining power, which in turn might affect the price. If this is the case and if our instrument is correlated with group heterogeneity, the estimate of the spillover effect might be biased. 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

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Table 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*** [0.017]	0.099** [0.038]	0.109*** [0.032]	239.0	[0.109, ∞)
Restricted sample						
Selling the best quality sample	179	0.146*** [0.016]	0.112*** [0.024]	0.118*** [0.023]	171.9	[0.118, ∞)
Selling to miller sample	203	0.110*** [0.018]	0.068 [0.037]	0.071** [0.033]	407.2	[0.071, ∞)
Selling to trader sample	116	0.136*** [0.025]	0.096* [0.048]	0.119*** [0.042]	120.2	[0.119, ∞)
Selling wet paddy sample	217	0.119*** [0.012]	0.110*** [0.024]	0.112*** [0.021]	110.4	[0.112, ∞)
Selling in November sample	190	0.133*** [0.030]	0.127*** [0.036]	0.124*** [0.033]	112.1	[0.127, ∞)
Single miller in the area sample	240	0.159** [0.047]	0.088 [0.047]	0.099** [0.039]	96.3	[0.099, ∞)
Selling the best quality wet paddy to miller in November sample	59	0.156*** [0.020]	0.156*** [0.035]	0.161*** [0.033]	72.1	n.a

Note: Standard errors are clustered by cooperatives and reported between brackets below the estimates. *, **, *** indicate significance at the 0.1, 0.05, 0.01 levels, respectively.

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 the treatment variable on farm size, we also get a negative coefficient, this time with t-value of –5.3. Therefore, both the variables satisfy the IIV assumption. Table 8, column (5) reports our results generated by 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 the variable "selling in treated areas." 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.

7. Policy implications

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, relative to nonparticipating 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 nonmember 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.

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 future evaluations of marketing cooperatives' 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.

CRediT authorship contribution statement

Kaittisak Kumse: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Visualization, Project administration. **Nobuhiro Suzuki:** Conceptualization, Methodology, Validation, Formal analysis, Resources, Writing - review & editing, Supervision, Funding acquisition. **Takeshi Sato:** Conceptualization, Methodology, Validation, Formal analysis, Resources, Writing - review & editing, Supervision, Funding acquisition. **Matty Demont:** Methodology, Validation, Formal analysis, Resources, Writing - review & editing, Supervision, Visualization, Funding acquisition.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

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

Table A1

Table A1
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).

Appendix B. Spillover effects of marketing cooperatives using restricted samples

Table B1-B7

Table B1
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
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
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
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
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
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
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.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2021.102051.

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