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FACTEURS SOCIAUX ET ADOPTION DE L'AGRICULTURE BIOLOGIQUE : APPORT DE L'ANALYSE ECONOMIQUE

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General introduction

The primary objective of this thesis is to study the adoption of organic agriculture from conventional agriculture by comprehensively analyzing the economic factors. We adopt the definition of *organic agriculture* as an agricultural method that prohibits the use of pesticides and other chemical substances, genetically modified products, and products originating from radiated substances. Organic agriculture reduces the harmful effects of agricultural activities on the environment, such as water pollution, and provides safe and healthy human food. It produces higher quality products than conventional methods. People can also trace the origin of organic products. This is a standard definition in the relevant literature and a principle in many countries' regulations (Willer et al., 2024). This definition helps the research generalize the adoption decision without limiting it to a specific national or regional certification requirement.

Conventional agriculture and its problems

The term *conventional agriculture* here is presented as a control or a comparative practice to sustainable agriculture, such as conservation agriculture, regenerative agriculture, or organic agriculture (Sumberg and Giller, 2022). This section clarifies what *conventional agriculture* means precisely throughout the succeeding chapters. In related studies on organic agriculture, the standard definition of conventional methods includes three characteristics: (1) production focusing on high levels of output, (2) failure to meet organic agricultural requirements, and (3) high dependence on external inputs (De Ponti et al., 2012; Pimentel and Burgess, 2014; Seufert et al., 2012; Shennan et al., 2017). In conventional agriculture, farmers cultivate crops intensively with very short rotation periods on farming lands and use chemical products such as fertilizers and various types of pesticides and herbicides to eliminate production risks and achieve high yields.

Conventional agriculture gains its prevalence due to its very high and stable yield, which safeguards the economic benefits for farmers who adopt these methods and secures food production, doubling over the past 60 years (Wittwer et al., 2021). However, this practice's economic and social costs are beginning to outweigh its benefits, resulting in alarming consequences for human beings and the environmental system. For example, overusing pesticides and herbicides causes public health problems, costing approximately 12 billion dollars annually in the United States (Pimentel and Burgess, 2014). In developing countries, for example, Vietnam, 85% Vietnamese farmers surveyed in Berg and Tam (2018) reported health problems related to chemical inputs. This practice adversely impacts biodiversity and ecosystem services through large-scale deforestation and chemical exposure to natural habitats (Wittwer et al., 2021). In the long term, it can lead to the extinction of some species, loss of natural evenness, and even pest outbreaks (Crowder et al., 2010). Additionally, this type of farming accelerates soil erosion, leading to degraded soil quality (Knapp and van der Heijden, 2018). Thus, sustainable agricultural practices are necessary to reduce these adverse effects and balance the food production system with the environmental network.

Organic agriculture and its advantages

Organic agriculture prohibits using pesticides, herbicides, and chemical fertilizers in the production system to guarantee the well-being of farmers directly exposed to these inputs. Converting from conventional to organic agriculture improves environmental indicators such as soil quality, biodiversity, and ecosystems (Eyhorn et al., 2019; Tuomisto et al., 2012). In particular, Muller et al. (2017) build different scenarios on the conversion level to organic agriculture under the assumption of climate change and the world food system. They show that adoption helps to reduce pressure on biodiversity while positively improving soil quality. These results are confirmed in the study by Wittwer et al. (2021). Their study states that organic farming positively impacts soil variables such as soil biodiversity, soil stability, and the presence of biota such as earthworms. Based on their findings, the authors further claim that increasing the amount of arable land dedicated to organic agriculture is necessary to protect the environment.

However, the conversion to organic agriculture is controversial in terms of productivity. Generally, many studies compare yields between the two alternatives, showing that organic agriculture's yield is lowered by 8 to 25% (Reganold and Wachter, 2016). Pest management issues can explain the lower yield, as pesticides are efficient inputs, and lower nutrient levels in the soil, which require farmers to use synthetic fertilizers (Tuomisto et al., 2012). These problems raise two arguments against organic agriculture: (1) it may not guarantee food security, and (2) it may pose a risk to farmers' economic benefits.

Some studies respond to the first argument by showing that organic yields could approach those of conventional agriculture if farmers learn to manage soil quality and use organic inputs, which have been shown to stabilize yields (Knapp and van der Heijden, 2018; Reganold and Wachter, 2016; Seufert et al., 2012; Tuomisto et al., 2012). Furthermore, organic yields vary by crop type. For example, Knapp and van der Heijden (2018) demonstrate that organic rice yields can be more stable than conventional ones, while Reganold and Wachter (2016) mention that soybean and corn yields do not differ significantly from their conventional counterparts.

From an economic perspective, the lower yield in organic practices is compensated by a price premium of about 29% to 30% (Reganold and Wachter, 2016). To break even with conventional agriculture, the break-even price needs to be about 5 to 7% higher than conventional prices. Thus, with a stable price premium in the market, farmers could generate higher revenues from adopting organic methods (Crowder and Reganold, 2015). Additionally, the actual costs of conventional agriculture have not accounted for its negative externalities on the environment, referred to as environmental costs. If these environmental costs are included, organic products could be more competitive than conventional ones (Crowder and Reganold, 2015; Reganold and Wachter, 2016).

The adoption challenges of organic agriculture

Total organic lands account for nearly 2% of the world's total arable lands (Willer et al., 2024). The limited uptake of organic farming can be attributed to the challenges farmers face in transitioning to these practices, primarily due to yield fluctuations and higher productivity risks compared to conventional methods. Economic factors, such as premium prices, strongly influence farmers' decision-making but are not guaranteed for farmers in developing countries, where small-scale farming predominates (Jouzi et al., 2017). Consequently, risk-averse farmers in developing countries often stick with conventional practices, limiting the adoption of organic methods. Thus, Chapter 3 of the thesis introduces a theoretical model for adoption by farmers under risk situations and provides a mechanism for information diffusion. Farmers cooperate through a Nash-bargaining model to overcome incomplete information and promote organic lands at optimal levels.

Among developing countries, Vietnam, primarily an agricultural nation, spans approximately 40% of total land for agricultural activities, and its agricultural land is characterized by small parcels, with nearly 70% being less than 0.5 hectares and 25% ranging from 0.5 to 2 hectares. Over the years of high agricultural productivity, the country has suffered the adverse effects of conventional agriculture. However, the adoption level of organic agriculture is still low, with nearly 1.5% total agricultural land. Vietnamese farmers still predominantly engage in conventional practices, which rely heavily on chemical pesticides and fertilizers to enhance yields and profits due to the ease of application and low labor requirements (Richter et al., 2015). There has been a noticeable increase in imported pesticides from 100 tons per year in 2002 to over 103,000 tons in 2012 (Berg and Tam, 2018). The use of synthetic substances, such as pesticides, often leads to adverse consequences such as increased insect resistance, posing significant health risks to both farmers and consumers in the long term: approximately two million Vietnamese farmers have been affected by health issues associated with pesticide and fertilizer exposure (Thai et al., 2017). Additionally, the environment faces severe threats from the adverse effects of chemical inputs, leading to environmental degradation, which could reduce long-term productivity and profits, while Vietnamese rice farmers who practice low-use pesticides experienced a stable and higher net income than the conventional groups (Berg and Tam,

2018).

Recognizing the future threats to national agriculture, the Vietnamese government firmly supports the transition to more sustainable practices, such as organic agriculture. In 2020, they approved the "*Project for the Development of Organic Agriculture Phase 2020-2030*" (Vietnamese Goverment, 2020). This project sets comprehensive goals for the nationwide adoption of organic agriculture. For example, the government aims to increase organic farming land to 3% of the total farming land by 2030, nearly doubling the land area from 2022. Additionally, organic rice cultivation is planned to expand from 70,000 hectares to 150,000 hectares by 2030, while organic vegetable cultivation is expected to increase from 10,000 to 20,000 hectares.

Given the current low adoption levels of organic farming in Vietnam and the substantial demand for adoption (around 1.5% of farming land), we focus on empirically examining the factors that play important roles in the adoption decisions of Vietnamese farmers through Chapter 2 and Chapter 4. Chapter 2 employs a quantitative approach using a discrete choice experiment involving 586 farmers in Northern Vietnam to gauge the effect of market and non-market factors on their preferences regarding participation in organic certification schemes. In Chapter 4, through a field experiment in Northern Vietnam, we explore the impact of information sharing and cooperation among farmers on introducing organic agriculture. The lack of information about organic technology hinders land allocation for organic agriculture, as we have observed.

Adopting organic production cannot be achieved without a shift in food consumption behaviors (Muller et al., 2017). Consumer demand plays a crucial role in stabilizing the price premium in the organic market and stimulating production from farmers. However, organic food consumption remains relatively low due to its higher price, limited availability, and consumer trust issues (Tarkiainen and Sundqvist, 2005). To address this, we utilize meta-regression analysis to assess the average quantified impact of social norms on the preference for organic food. Additionally, we examine publication bias within the research domain in Chapter 1.

We are resuming the four chapters in the following sections:

Chapter 1 - Social norms and organic food adoption: A meta-regression analysis (*co-author: P. Nguyen-Van*)

Organic food consumption remains low due to its higher price, limited availability, and consumer confidence (Tarkiainen and Sundqvist, 2005). Various research projects have explored the factors influencing organic food consumption (Aertsens, Verbeke, Mondelaers, and Van Huylenbroeck, 2009a). Social norms pertaining to noticeable factors relating to peers or others are examined because they play a significant role in behavioral intention (Ajzen, 1991; Cialdini and Trost, 1975; Robinson et al., 2014). This chapter delves into meta-regression analysis to analyze the average quantified impact of social norms on the choice of organic food and to test for potential publication bias in the research field (Brodeur and Sangnier, 2016; H. Doucouliagos and Stanley, 2009).

Meta-regression analysis systematically reviews existing research on social norms and organic food choices. This technique has been proven effective in the economic field for investigating the prevalence of publication bias and explaining the diversification of effect sizes (H. Doucouliagos et al., 2014; Gurevitch et al., 2018). Scalco et al. (2017) conducted a meta-analysis study on organic food choices to justify the antecedents of organic food choice from the Theory of Planned Behavior. According to the study, social norms and attitudes significantly impact the buying intention of organic food, while perceived controlled behavior has a more minor impact. Our study differs from Scalco et al. (2017) by utilizing meta-regression analysis and converting the regression coefficient to a partial correlation coefficient instead of Pearson's correlation. We enhance the research by investigating the presence of publication bias and exploring the significant characteristics of studies related to the results. Massey et al. (2018) conducted a meta-analysis to examine the factors influencing the purchase of organic food, focusing on attributes such as health benefits, quality, taste, and environmental friendliness. However, social norms were not investigated in their research. Our study complements the meta-analysis studies of Scalco et al. (2017) and Massey et al. (2018) by analyzing social norms through meta-regression.

We find a positive correlation between social norms and the adoption of organic food. This outcome suggests the potential for future policies to leverage social influences as consumer incentives. Furthermore, integrating social influence with other factors, such as attitude and perceived control behaviors, is essential to ensure a sustained impact on people's behaviors (Hornik et al., 1995).

Chapter 2 - Farmers' preferences toward organic certification scheme: Evidence from a discrete choice experiment in Northern Vietnam (*co-authors: K. Boun My, P. Nguyen-Van, T.K.C Pham, A. Stenger, T. Tiet, N.T. To*)

The existing literature indicates that farmers' transition to organic farming is influenced by various market and political factors, including agricultural policy, market structure, and technological design (Jaime et al., 2016). Market obstacles, such as slow market expansion for organic products and the absence of a certification system, have been identified as hurdles that must be addressed to promote the adoption of organic farming practices Schneeberger et al., 2002). Providing adequate information about the benefits and standards of organic products has been suggested as a strategy to reduce marketing costs and, consequently, lower the price of organic goods. Therefore, implementing organic certification schemes could potentially ensure certified farmers a stable income by facilitating increased access to new markets and guaranteeing product price premiums (Sapbamrer and Thammachai, 2021).

Farmer networks play a crucial role in motivating the conversion to organic farming: they serve as valuable sources of information, enabling farmers to exchange knowledge and share social preferences, as most farmers are part of local networks, such as those comprised of neighborhood farmers, friends, or agricultural organizations in their area (Nguyen-Anh et al., 2022). Several studies have indicated that farmers are more likely to access information about dairy farming through their interpersonal social networks, leading to improved learning and productivity (BenYishay and Mobarak, 2019). Additionally, frequent communication and discussions with neighboring farmers have been found to significantly promote the adoption of organic farming (Unay Gailhard et al.,

2015).

While many studies have concentrated on farmers' willingness to accept (WTA) changes in revenue and incentive payments to transition to organic farming, there is limited evidence regarding farmers' willingness to pay (WTP) for changes in production costs associated with engaging in organic certification schemes, as well as the influence of networks (such as adoption decisions of neighboring farmers and local village leaders) on farmers' preferences toward organic farming. Organic certification schemes play a crucial role in providing farmers with the opportunity to attain organic labeling, which helps meet the growing consumer demand, signal environmentally friendly practices, differentiate their products in competitive markets, and access new markets with guaranteed product prices. This chapter addresses this gap by examining farmers' preferences and willingness to pay for changes in production costs associated with participating in organic certification schemes using a *discrete choice experiment*. Specifically, we seek to shed light on farmers' preferences for a hypothetical organic certification scheme, considering various market attributes (such as sales contracts and logos with traceable codes) and non-market attributes (including the role of networks, involvement of local leaders, and provision of training and technical assistance), and estimate their economic value in terms of marginal willingness to pay (WTP).

Chapter 3 - Cooperation in organic agriculture adoption: A theoretical model

This chapter addresses the challenges of adopting organic agriculture, as outlined in the preceding sections. Farmers face a situation where they can transition their land to a new agricultural type, potentially relinquishing their conventional practices. Yet, they lack sufficient information to guarantee the outcomes of their decisions. Numerous studies have supported the concept of the "first-mover" in decision-making scenarios characterized by risks or incomplete information (Potters et al., 2005, 2007; Vesterlund, 2003). We construct models wherein one farmer is assigned as the leader, acting as the first-mover, to decide how to allocate their land to organic farming first. Other followers in the group observe and then make their own decisions.

We aim to investigate whether leadership influences farmers' decisions to adopt organic agriculture. Our model posits that leaders who possess superior information than farmers and are willing to share it can assist farmers in making better decisions. We introduce Nash's bargaining model for negotiation between leaders and followers to compensate for the leadership's information. Our findings indicate that farmers are willing to share half of the benefits with the leader in exchange for access to the information.

Our study underscores the significance of equipping farmers with information as a pivotal strategy to alleviate apprehensions and encourage the adoption of organic agriculture. Nevertheless, our model emphasizes the influence of "informal leaders" who possess early access to information compared to other farmers. We propose that these informal leaders can serve as central figures for disseminating information throughout networks, as discussed in Beaman et al. (2021).

Chapter 4 - Nash-bargaining model in organic agriculture's adoption: Lab-in-field experiment in Northern Vietnam (*co-authors: K. Boun My, P. Nguyen-Van, A. Stenger, N.T. To*)

The chapter focuses on production risk, which pertains to the risk in productivity affecting farmers' income (Bontemps et al., 2021). This risk is heightened in the absence of experience in organic farming. Disseminating information on organic agriculture enhances farmers' knowledge and expertise, easing the transition to new methodologies. Evidence suggests that information diffusion positively influences farmers' decision-making, as evidenced by increased adoption rates in randomized controlled experiments (BenYishay and Mobarak, 2019).

We conducted a lab-in-field experiment to investigate the effect of information sharing among risk-averse farmers on adopting organic agriculture. Using the definition of risk from previous studies (Bougherara et al., 2017), we quantify risk by calculating the objective probabilities of all possible states of nature that farmers are familiar with, which impact their adoption decisions. In our experiment, farmers interact in pairs, deciding how much land to allocate to conventional and organic agriculture. The 'leader' farmer, possessing superior information, initiates decision-making before the follower. A follower can observe a leader's decision and then decide. The Nash-Bargaining model (Nash, 1953) is utilized to model the shared information, allowing us to create a cooperative game between two farmers that benefits from sharing information.

Farmers make allocations in three scenarios. In scenario 1, farmers have complete and symmetric information about organic technology. In scenario 2, only the leader has complete information about organic technology; the follower does not know about organic technology, and there is no bargaining stage. Scenario 3 is the same as scenario 2, but two farmers can join a bargaining stage to share the information and the potential benefits.

The study's results validate theoretical predictions, with over 80% of farmers engaging in bargaining in scenario 3. There is a significant demand among farmers for information-seeking when confronted with risks in agricultural activities. The model aligns well with empirical studies, indicating that farmers are more inclined to seek information from fellow farmers within their communities. Moreover, informed farmers play a crucial role in disseminating information and influencing adopting new practices such as organic agriculture. These findings advocate for an information diffusion policy approach to promote organic agriculture rather than traditional methods such as service extensions.

Introduction générale

L'objectif principal de cette thèse est d'étudier l'adoption de *l'agriculture biologique* à partir de l'agriculture conventionnelle en analysant de manière exhaustive les facteurs économiques. Nous adoptons la définition de l'agriculture biologique comme méthode agricole qui interdit l'utilisation de pesticides et d'autres substances chimiques, les produits génétiquement modifiés et les produits d'origine des substances irradiées durant la procédure de la production. L'agriculture biologique réduit les effets nuisant des activités de l'agriculture à l'environnement : la pollution de l'eau. En outre, les produits biologiques sont sains pour la santé des humaines. La qualité de produit de l'agriculture biologique est, en général, meilleure que celle de l'agriculture conventionnelle. En outre, on peut retracer de l'origine de produits biologiques facilement.

On retrouve cette définition dans les études concernant ces sujets, ainsi que le principe fondamental de régulation nationale et régionale comme l'Union européenne (Willer et al., 2024). Cette définition permettra une généralisation des décisions d'adaptation sans aucune restriction sur la réglementation d'un pays ou d'une région.

L'agriculture conventionelle et ses problèmes

La notion *l'agriculture conventionnelle* représente une méthode de comparaison avec les agricultures durables, telles que l'agriculture conservation, l'agriculture régénérative et l'agriculture biologique (Sumberg and Giller, 2022). Cette section clarifie donc la signification précise de l'agriculture conventionnelle utilisée dans les chapitres successifs. Trois points sont la définition commune de la méthode conventionnelle parmi les étudiants liés : (1) une production se focalisant sur les rendements élevés, (2) Absence de critères pour l'agriculture biologique, et (3) une dépendance importante envers des intrants extérieurs, notamment les produits chimiques (De Ponti et al., 2012; Pimentel and Burgess, 2014; Seufert et al., 2012; Shennan et al., 2017). Pour faire l'agriculture conventionnelle, les agricultures donc cultivent intensivement sur les cultures avec une rotation très courte sur leur terrain ainsi qu'utilisent des produits chimiques comme les engrais et les pesticides ainsi que les herbicides afin d'épargner les risques de production et d'assurer les quantités élevées.

Le rendement très élevé et stable de l'agriculture conventionnelle maintient sa notoriété, préservant les avantages économiques pour les agriculteurs qui adoptent ces méthodes, et assurant la sécurité de la production alimentaire qui a doublé depuis plus de 60 ans (Wittwer et al., 2021). Pourtant, les coûts économiques et sociaux de cette méthode sont en train de surpasser ces avantages, et causent des conséquences indésirables envers les humains ainsi que l'environnement. Par exemple, l'utilisation excessive de pesticides et d'herbicides a provoqué des problèmes de santé importants, ce qui a coûté environ douze millions de dollars chaque année aux États-Unis (Pimentel and Burgess, 2014). Parmi des pays en développements, par exemple Vietnam, 85 pour cents des agriculteurs vietnamiens interrogés ont fait part de problèmes de santé liés aux intrants chimiques (Berg and Tam, 2018. La pratique a des répercussions négatives sur la biodiversité et les services écosystémiques, en raison de la déforestation importante et de l'exposition à des produits chimiques dans les habitats naturels (Wittwer et al., 2021). Sans aucun changement à long terme, cette méthode pourrait causer un certain risque d'extinction des insectes, ce qui entraînerait la perte de l'équilibre naturel et entraînerait un flux d'insectes nuisibles (Crowder et al., 2010). En outre, cela provoque une augmentation de l'érosion du sol, ce qui aura un impact significatif sur la qualité des sols (Knapp and van der Heijden, 2018). En conséquence, la société dans son ensemble a pris conscience des effets négatifs de l'agriculture conventionnelle et de la nécessité de réorienter les méthodes de production agricoles vers la prise en compte des aspects environnementaux et sanitaires..

L'agriculture biologique et ses avantages

L'interdiction d'employer des produits chimiques a aussi des avantages pour les agriculteurs directement en contact avec ces produits nocifs. De plus, une conversion de l'agriculture conventionnelle à l'agriculture biologique aide à réparer et renforcer les éléments d'environnement tels que la qualité du sol, la biodiversité, ainsi que l'écosystème (Eyhorn et al., 2019; Tuomisto et al., 2012). En particulier, Muller et al. (2017) ont développé des scénarios différents sur les niveaux de conversion en fonction des conditions supposées du changement climatique et du système alimentaire mondial. Ils prouvent que l'adoption de l'agriculture biologique permet de diminuer la pression sur la biodiversité et d'améliorer positivement la qualité du sol. De même manière, les résultats de l'étude de Wittwer et al. (2021) montrent que la culture biologique a les impacts positifs sur les indicateurs du sol tels que la biodiversité du sol, la stabilité du sol, ainsi que la meilleure présence de biotes comme le verre de terre, etc. En se basant sur leurs résultats, les auteurs soutiennent l'importance d'accroître les terres cultivables en l'agriculture biologique pour préserver l'environnement.

Cependant, la conversion fait l'objet de sérieuses discussions sur sa productivité. En général, une certaine d'études, faisant les rapports sur les rendements entre deux méthodes alternatives, montrent que les rendements de l'agriculture biologique sont moins hauts que ceux de l'agriculture conventionnelle, de huit pour cent à vingt-cinq pour cent (Reganold and Wachter, 2016). Ces bas rendements seraient dues aux mises en œuvre en particulier de la gestion des parasites, insectes et autres nuisibles. (Tuomisto et al., 2012). Ces problèmes posent deux arguments principaux envers l'agriculture biologique :

(1) L'agriculture biologique ne pourrait pas assurer le système alimentaire ;

(2) L'agriculture biologique évoque les risques considérables sur les revenus de l'agriculteurs.

Premièrement, certaines études ont montré que la productivité de l'agriculture biologique pourrait augmenter au niveau celui de l'agriculture conventionnelle si l'agriculteur apprend à mieux gérer la qualité de sol ainsi que fabrique les intrants biologiques afin de stabiliser et accroît les rendements (Knapp and van der Heijden, 2018;

Reganold and Wachter, 2016; Seufert et al., 2012; Tuomisto et al., 2012).En plus, les rendements sont déterminés dépendent du type de culture. Knapp and van der Heijden (2018) prouvent que le rendement du riz biologique est plus stable que celui de l'agriculture conventionnelle alors que le Reganold and Wachter (2016) indique que le rendement du soja et du maïs bio est au niveau des rendements en agriculture conventionnelle. Par conséquent, l'agriculture biologique pourrait atteindre un niveau de rendement élevé pour contribuer de manière significative au système alimentaire.

Deuxièmement, le niveau bas de rendements de l'agriculture biologique serait compensé par le prix premium, qui se situe entre vingt-neuf pour cent et trente pour cent (Reganold and Wachter, 2016). En réalité, pour maintenir un équilibre économique avec l'agriculture conventionnelle, il faut que le prix de produits de l'agriculture biologique soit supérieur d'environ 5 à 7% aux prix des produits de l'agriculture conventionnels (Crowder and Reganold, 2015). Si le prix premium est stable sur le marché, l'agriculteur gagnerait mieux en s'adaptant à l'agriculture biologique.

Enfin, les coûts de l'agriculture conventionnelle actuelle ne prennent pas en considération les externalités négatives, à savoir les coûts environnementaux. Si ces coûts sont pris en considération, les produits provenant de l'agriculture biologique seraient plus compétitifs que ceux provenant de l'agriculture conventionnelle (Crowder and Reganold, 2015; Reganold and Wachter, 2016).

Les défis d'adaptation de l'agriculture biologique

Les terres cultivables mondial pour l'agriculture biologique ne comptent que deux pourcents(Willer et al., 2024). L'adoption limitée de l'agriculture biologique peut être attribuée aux difficultés rencontrées par les agriculteurs lors de la transition vers ces pratiques, principalement en raison des fluctuations des rendements : risques de productivité plus élevés que les méthodes conventionnelles. Les facteurs économiques, tels que les prix premium qui influencent fortement la prise de décision des agriculteurs, ne sont pas garantis pour les agriculteurs des pays en développement, qui font principalement l'agriculture à petite échelle (Jouzi et al., 2017). C'est pourquoi les agriculteurs des pays en développement, qui ont peur du risque, ont souvent décidé de suivre les pratiques conventionnelles, ce qui restreint l'adoption de méthodes biologiques. Ainsi, le Chapitre 3 de la thèse introduit un modèle théorique pour l'adoption par les agriculteurs en situation de risque et fournit un mécanisme pour informer la diffusion que les agriculteurs coopèrent à travers un modèle de négociation pour surmonter l'information incomplète et promouvoir les terres biologiques à des niveaux optimaux.

Parmi les pays en développement, le Vietnam, principalement un pays agricole, couvre environ 40 pour cents de la superficie totale des terres destinées aux activités agricoles, et ces terres agricoles caractérisent les petites parcelles, avec près de 70 pour cents étant moins de 0,5 hectare et 25 pour cents, de 0,5 à 2 hectares. Au cours des années de productivité agricole élevée, le pays souffre de l'effet négatif de l'agriculture conventionnelle, pourtant le niveau d'adoption de l'agriculture biologique est encore faible, près de 1,5 pour cents des terres agricoles totales. En fait, les agriculteurs vietnamiens continuent de pratiquer principalement des méthodes conventionnelles, qui reposent fortement sur les pesticides chimiques et les engrais afin d'améliorer les rendements et les bénéfices grâce à des facilités d'application et faibles besoins en main-d'œuvre (Richter et al., 2015). Il y a eu une augmentation notable des pesticides importés, passant de 100 tonnes par an en 2002 à plus de 103 000 tonnes en 2012 (Berg and Tam, 2018). En outre, l'utilisation de substances synthétiques, telles que les pesticides, entraîne souvent des conséquences néfastes telles qu'une résistance accrue aux insectes, ce qui pose des risques sanitaires importants pour les agriculteurs et les consommateurs à long terme : l'exposition aux pesticides et aux engrais a causé des problèmes de santé à environ deux millions d'agriculteurs vietnamiens (Thai et al., 2017). En outre, l'environnement est confronté à de graves menaces dues aux effets néfastes des intrants chimiques, ce qui conduit à une dégradation de l'environnement qui pourrait réduire la productivité et les profits à long terme, tandis que les riziculteurs vietnamiens qui utilisent moins de pesticides ont connu un revenu net stable et supérieur à celui des groupes conventionnels (Berg and Tam, 2018).

Conscient des menaces futures sur l'agriculture nationale, le gouvernement vietnamien soutient fermement la transition vers une agriculture plus durable telle que l'agriculture biologique : ils ont approuvé le "*Projet pour le développement de l'agriculture* *biologique Phase 2020-2030"* en 2020 (Vietnamese Goverment, 2020). Ce projet construit des objectifs pour une adoption complète de l'agriculture biologique au niveau national, par exemple, le gouvernement vise à augmenter les terres agricoles biologiques à 3 pour cents de la superficie agricole totale en 2030, ce qui doublera les terres à partir de 2022. En détail, les rizières biologiques prévoient de passer de 70 000 hectares à 150 000 hectares en 2030, tandis que celles des légumes biologiques passeront de 10 000 à 20 000 hectares.

Compte tenu des faibles taux d'adoption de l'agriculture biologique (environ 1,5 pour cents des terres agricoles) au Vietnam et de la forte demande d'adoption, nous nous concentrons sur l'examen empirique des facteurs jouant un rôle important dans la décision d'adoption des agriculteurs vietnamiens par les Chapitre 2 et Chapitre 4. Le Chapitre 2 utilise une approche quantitative par le biais d'une expérience de choix discrets impliquant 586 agriculteurs du nord du Vietnam pour évaluer l'effet des facteurs du marché et non du marché sur leurs préférences en matière de participation aux programmes de certification biologique par le biais d'une expérience de terrain dans le nord du Vietnam. Dans le Chapitre 4, on examine l'effet du partage d'informations et de la coopération entre agriculteurs sur l'introduction de l'agriculture biologique. Nous avons remarqué que le manque d'informations sur la technologie biologique constitue un obstacle à l'attribution des terres pour l'agriculture biologique.

L'adoption en production biologique nécessite un changement des comportements de consommation alimentaire (Muller et al., 2017). La demande des consommateurs maintient la prime de prix sur le marché biologique et encourage la production des agriculteurs. Néanmoins, la consommation d'aliments biologiques demeure relativement faible en raison de facteurs comme son prix plus élevé, sa disponibilité limitée et les problèmes de confiance des consommateurs (Tarkiainen and Sundqvist, 2005). Nous donc utilisons une analyse de méta-régression pour évaluer l'impact moyen quantifié des normes sociales sur la préférence pour les aliments biologiques et examiner ensuite la présence de biais de publications dans le domaine de la recherche au Chapitre 1.

L'introduction les chapitres

Nous allons présenter les chapitres de cette thèse ci-dessous :

Chapitre 1 - Normes sociales et adoption d'aliments biologiques : une analyse de méta-régression (*co-auteur: P. Nguyen-Van*)

Le prix plus élevé, la disponibilité et la confiance des consommateurs ont entraîné une faible consommation d'aliments biologiques (Tarkiainen and Sundqvist, 2005). Plusieurs études ont porté sur les facteurs qui influent sur la consommation d'aliments biologiques (Aertsens, Verbeke, Mondelaers, and Van Huylenbroeck, 2009a). Les normes sociales, des facteurs notables qui se rapportent aux pairs ou à d'autres personnes, sont examinées parce qu'elles sont essentielles à l'intention comportementale (Ajzen, 1991; Cialdini and Trost, 1975; Robinson et al., 2014). Ce chapitre explore l'analyse de méta-régression pour analyser l'impact moyen quantifié des normes sociales sur le choix des aliments biologiques et tester ensuite s'il existe un problème de biais de publication dans le domaine de la recherche (Brodeur and Sangnier, 2016; H. Doucouliagos and Stanley, 2009).

L'analyse de méta-régression implique une revue exhaustive des études existantes sur les normes sociales et les choix alimentaires biologiques. Dans le domaine économique, cette méthode a été efficace pour étudier la prévalence du biais de publications et expliquer la diversification des tailles d'effet (H. Doucouliagos et al., 2014; Gurevitch et al., 2018). Scalco et al. (2017) ont réalisé une méta-analyse sur les décisions alimentaires biologiques pour expliquer les origines des choix alimentaires biologiques dans la théorie du comportement planifié. D'après l'étude, les normes sociales et les attitudes ont un impact significatif sur l'envie d'acheter des aliments biologiques, mais les comportements contrôlés perçus ont un impact faible. Dans notre étude, nous utilisons l'analyse de méta-régression, ce qui la différencie de Scalco et al. (2017). Plutôt que la corrélation de Pearson, nous transformons le coefficient de régression en un coefficient de corrélation partiel. Pour améliorer la recherche, nous examinons la présence de biais de publication, puis nous examinons les caractéristiques importantes des études liées aux résultats. Massey et al. (2018) ont réalisé une méta-analyse pour évaluer les facteurs qui influencent l'achat d'aliments biologiques. La recherche fournit une analyse complète des attributs des aliments biologiques (biens de santé, qualité, goût et respectueux de l'environnement, etc.) sur l'achat d'aliments biologiques, mais les normes sociales n'ont pas intégrées dans leur recherche. Notre étude est complémentaire aux études de méta-analyse de Scalco et al. (2017) and Massey et al. (2018) en ce sens qu'elle analyse les normes sociales par méta-régression.

Nous remarquons un lien positif entre les normes sociales et l'adoption d'aliments biologiques. Ce résultat ouvre la voie à de futures politiques visant à exploiter les influences sociales dans l'encouragement des consommateurs. De plus, l'intégration de l'influence sociale à d'autres facteurs comme l'aptitude, les comportements de contrôle perçus, etc., est essentielle pour assurer un impact durable sur les comportements des gens (Hornik et al., 1995).

Chapitre 2 - Préférence des agriculteurs envers le système de certification biologique : preuve d'une expérience de choix discrets dans le nord du Vietnam (*co-auteurs: K. Boun My, P. Nguyen-Van, T.K.C Pham, A. Stenger, T. Tiet, N.T. To*)

La documentation existante indique que la transition des agriculteurs vers l'agriculture biologique est influencée par un éventail de facteurs commerciaux et politiques, y compris la politique agricole, la structure du marché et la conception technologique (Jaime et al., 2016). Les obstacles au marché, tels que la lenteur de l'expansion du marché des produits biologiques et l'absence de systèmes de certification, ont été identifiés comme des obstacles à surmonter pour promouvoir l'adoption de pratiques d'agriculture biologique Schneeberger et al., 2002). Il a été suggéré de fournir une information adéquate sur les avantages et les normes des produits biologiques comme stratégie pour réduire les coûts de commercialisation et, par conséquent, baisser le prix des produits biologiques. Par conséquent, la mise en œuvre de systèmes de certification biologique pourrait potentiellement assurer aux agriculteurs certifiés un revenu stable en facilitant l'accès à de nouveaux marchés et en garantissant des primes de prix pour leurs produits (Sapbamrer and Thammachai, 2021).

Les réseaux d'agriculteurs jouent un rôle crucial dans la conversion vers l'agriculture biologique : ils servent de sources d'informations précieuses, permettant aux agriculteurs d'échanger des connaissances et de partager des préférences sociales, car la plupart des agriculteurs font partie des réseaux locaux, tels que ceux composés d'agriculteurs de quartiers, d'amis ou d'organisations agricoles dans leur région (Nguyen-Anh et al., 2022). Plusieurs études ont indiqué que les agriculteurs sont plus susceptibles de réussir à obtenir de l'information sur la production laitière grâce à leurs réseaux sociaux interpersonnels, ce qui améliore l'apprentissage et la productivité (BenYishay and Mobarak, 2019). En outre, il a été constaté que la communication et les discussions fréquentes avec les agriculteurs voisins favorisent considérablement l'adoption de l'agriculture biologique (Unay Gailhard et al., 2015).

Alors que de nombreuses études se sont concentrées sur la volonté des agriculteurs d'accepter (VDA) les changements dans les revenus et les paiements d'incitations à la transition vers l'agriculture biologique, il y a peu de preuves concernant la volonté des agriculteurs de payer (VDP) pour les changements dans les coûts de production associés à l'engagement dans des systèmes de certification biologique, ainsi que l'influence des réseaux (tels que les décisions d'adoption des agriculteurs voisins et locaux chefs de village) sur les préférences des agriculteurs envers l'agriculture biologique. Les systèmes de certification biologique jouent un rôle crucial en offrant aux agriculteurs la possibilité d'obtenir un étiquetage biologique, ce qui contribue à répondre à la demande croissante des consommateurs, à signaler des pratiques respectueuses de l'environnement, à différencier leurs produits sur des marchés concurrentiels et accéder à de nouveaux marchés avec des prix garantis. Ce chapitre donc vise à combler cette lacune en examinant les préférences des agriculteurs et leur volonté de payer pour les variations des coûts de production associés à la participation à des systèmes de certification biologique en utilisant une expérience de choix discrets. Plus précisément, nous cherchons à mettre en lumière les préférences des agriculteurs pour un système hypothétique de certification biologique, en tenant compte de divers attributs du marché (tels que les contrats de vente et les logos avec des codes traçables) et des attributs non commerciaux (y compris le rôle des réseaux, la participation des dirigeants locaux et la fourniture de formations et d'assistance technique) et estimer leur valeur économique en termes de volonté marginale de payer (VDP).

Chapitre 3 - La coopération en agriculture biologique : un modèle théorique

Ce chapitre se focalise sur les défis liés à l'adoption de l'agriculture biologique, comme précisé dans les sections précédentes. Les agriculteurs se retrouvent dans une situation où ils ont la possibilité de transférer leurs terres vers un nouveau type d'agriculture, ce qui pourrait les amener à abandonner leurs pratiques conventionnelles, mais ils manquent d'informations suffisantes pour s'assurer des résultats de leurs décisions. De nombreuses études ont soutenu l'idée du 'premier venu' dans les situations de prise de décision caractérisées par des risques ou des informations incomplètes (Potters et al., 2005, 2007; Vesterlund, 2003). Nous mettons en place des modèles où un agriculteur est désigné comme un leader, un précurseur, qui décide en premier comment allouer ses terres à l'agriculture biologique. D'autres membres du groupe observent et décident ensuite par eux-mêmes.

Nous cherchons à savoir si le leadership a un impact sur les décisions des agriculteurs d'adopter l'agriculture biologique. Selon notre modèle, les dirigeants, qui ont une connaissance supérieure à celle des agriculteurs et sont prêts à la partager, peuvent aider les agriculteurs à prendre de meilleures décisions. Nous exposons le modèle de négociation de Nash pour une négociation entre les dirigeants et les partisans, dans le but d'échanger les informations manquantes. D'après nos résultats, les agriculteurs sont disposés à partager la moitié des avantages avec le leader, en échange de l'accès à l'information.

Notre étude met en évidence l'importance de fournir aux agriculteurs des informations comme stratégie essentielle pour atténuer les appréhensions et encourager l'adoption de l'agriculture biologique. Cependant, notre modèle met particulièrement l'accent sur l'impact des 'leaders informels' qui ont un accès rapide à l'information par rapport aux autres agriculteurs. Nous suggérons que ces dirigeants informels puissent jouer un rôle central dans la diffusion de l'information à travers les réseaux, comme spécifié dans Beaman et al. (2021).

Chapitre 4 - Modèle de négociation de Nash dans l'adoption de l'agriculture biologique : expérience de laboratoire sur terrain dans le nord du Vietnam (*co-auteurs: K. Boun My, P. Nguyen-Van, A. Stenger, N.T. To*)

Ce chapitre met l'accent sur le risque de production, qui est l'incertitude de la productivité affectant le revenu des agriculteurs (Bontemps et al., 2021). En l'absence d'expérience en agriculture biologique, le risque augmente. En diffusant des informations sur l'agriculture biologique, les agriculteurs peuvent améliorer leurs connaissances et leur expertise, ce qui facilite la transition vers de nouvelles méthodologies. Les preuves suggèrent que la diffusion de l'information a un effet positif sur la prise de décision des agriculteurs, comme en témoignent les taux d'adoption accrus observés dans les expériences contrôlées randomisées (BenYishay and Mobarak, 2019).

Nous avons réalisé une expérience de laboratoire sur le terrain afin d'analyser l'effet du partage d'informations entre les agriculteurs sur l'adoption de l'agriculture biologique (Bougherara et al., 2017). En utilisant la définition du risque des études précédentes, nous quantifions le risque en calculant les probabilités objectives de tous les états possibles de la nature que les agriculteurs connaissent et qui ont une incidence sur leurs décisions d'adoption. Dans notre expérience, il y a des agriculteurs qui interagissent entre eux, chacun choisissant la quantité de terres qu'il consacre à l'agriculture conventionnelle et biologique. L'agriculteur en position de leader possède une information supérieure et prend des décisions. Le modèle Nash-Bargaining (Nash, 1953) est employé pour représenter l'information partagée. En utilisant ce modèle, nous pouvons instaurer un jeu coopératif impliquant deux agriculteurs qui tirent parti du partage de l'information.

Les agriculteurs font des allocations dans trois scénarios. Dans le scénario 1, les agriculteurs ont des informations complètes et symétriques sur la technologie biologique. Dans le scénario 2, seul le leader a des informations complètes sur la technologie biologique

; le suiveur ne connaît pas la technologie biologique ; il n'y a pas de phase de négociation. Le scénario 3 est le même que le scénario 2, mais les deux agriculteurs peuvent participer à une phase de négociation pour partager les informations et les bénéfices potentiels.

Les conclusions de l'étude confirment les prédictions théoriques, avec plus de 80 pour cents des agriculteurs impliqués dans les négociations dans le scénario 3. Il est évident que les agriculteurs requièrent une grande quantité d'informations lorsqu'ils sont confrontés à des risques dans leurs activités agricoles. Le modèle est en parfaite adéquation avec les études empiriques, ce qui suggère que les agriculteurs sont plus enclins à chercher de l'information auprès d'autres agriculteurs dans leurs collectivités. De plus, les agriculteurs bien informés ont un rôle vital dans la diffusion de l'information et l'adoption de nouvelles pratiques telles que l'agriculture biologique. Ces résultats suggèrent une approche politique de diffusion de l'information pour encourager l'agriculture biologique, au lieu des méthodes traditionnelles telles que les extensions de services.

Chapter 1

Social norms and organic food adoption: A meta-regression analysis

This Chapter is from a paper working under the same name. The co-author of this paper is P. Nguyen-Van, ECONOMIX, CNRS & University of Paris Nanterre, France.

Summary

Organic food is a promising solution for the food safety and well-being of the environment, plants, animals, and humans. The choice of organic food has increased, yet the growth rate remains modest. Our study applies the meta-regression analysis on the impact of social norms on organic food adoption to draw a more robust and consistent conclusion on the role of social influences as an incentive for consuming organic food. The data is from all available papers on the relationship between the social impact of organic food. We combine 41 papers from different journals and have 122 observations. Our analysis supports the positive relationship between social norms and organic food adoption. We find out that differences in analysis designs, sampling methodology, and journal characteristics statistically explain the heterogeneity in interested estimates between 41 papers.

Keywords: Meta-regression analysis; Organic food; Social norm; Subjective norm.

JEL Classfication: D12.

1.1 Introduction

The increasing world population and improvements in the standard of life create a challenge in feeding the world with the most negligible negative impact on the natural environment. The organic food is one of the solutions to that challenge (Seufert et al., 2012). The amount of artificial chemical substances in organic food is undoubtedly safer than in conventional counterparts (Mie et al., 2017). Consumers also pay attention to the ethical aspects that illustrate their personal and moral beliefs in buying food products (Dowd and Burke, 2013). Those factors result in their adopting behavior toward organic food products to ascertain that organic food is good and safe for their health and satisfies their environmental concerns. Thus, the organic food market is becoming more important than the conventional food market in some countries nowadays (Biel et al., 2005).

Food consumption or practices play a central role in guiding an individual to a sustainable lifestyle and are the focal dimension for environmental policy. Therefore, research on organic food consumption is essential to understand consumer behavior at the micro level and draw an efficient environmental policy from the government for sustainable economic development. Many researchers have thoroughly studied the determinants of consumer behavior when choosing sustainable food products. They have based on the theories of consumer behaviors to employ the attitude, norms, environmental concerns, socio-economic factors, and demographic factors for explaining the purchasing decision (Aarset et al., 2004; Aertsens, Verbeke, Mondelaers, and Van Huylenbroeck, 2009b)

Organic agriculture positively impacts the natural environment and soil management (Altenbuchner et al., 2018). The yield in organic agriculture is considered lower than in conventional one, but the yield depends on management system and spatial factors (Milgroom et al., 2007; Seufert et al., 2012). In those views, organic food consumption helps maintain organic agriculture's growth.

However, organic food consumption is still relatively low because of its higher price, availability, and the consumer's trust (Tarkiainen and Sundqvist, 2005). The question of what factors have influenced organic food consumption has been raised and solved in several researches (Aertsens, Verbeke, Mondelaers, and Van Huylenbroeck, 2009a).

Social norms, external factors relating to peers or others, are analyzed because they play essential roles in behavioral intention (Ajzen, 1991; Cialdini and Trost, 1975; Robinson et al., 2014). There are three constructs for social norms: (1) subjective norm, (2) injunctive norm, and (3) descriptive norm. The subjective norm was introduced firstly in the Theory of Planned Behavioural model (Ajzen, 1991). This construct is the opinion of essential peers (family, friends, etc.) on a particular behavior. The subjective norm, attitude, and perceived behavioral control are three primary factors that explain purchasing intention in empirical studies (Aertsens, Verbeke, Mondelaers, and Van Huylenbroeck, 2009a; Arvola et al., 2008; Joshi and Rahman, 2015). The injunctive norm is the effect of the peer's opinions, but the construct is not limited to the degree of importance of peers (Cialdini et al., 1990). Subjective and injunction norms indicate what should or should not behave. The descriptive norm answers the question of what other people do. This norm is the effect of the fundamental behavior of others on our behavioral intention (Cialdini et al., 1990). Different constructs of social norms are perceived, actual, prescriptive, and proscriptive norms. However, the three constructs in our study are used in most of the pro-environmental behavior research (Farrow et al., 2017). In pro-environmental behavior, the significant influence of social norms has been empirically justified through experimental research (Farrow et al., 2017).

Social norms guide deciding which behavior occurs in the eating habit or food consumption (Robinson et al., 2014). In the research on organic food, Aertsens et al. (2009) (Aertsens, Verbeke, Mondelaers, and Van Huylenbroeck, 2009a) conduct a review of the personal factors and the consumption of organic food. Most researches show positive quantified values on the relationship between social norms and purchasing intention toward organic food (Khare, 2015; Liang, 2016). A few studies have negative or insignificant results (Al-Swidi et al., 2014; Testa et al., 2019). The social norms also have an indirect relationship with *purchasing intention* through the *attitude toward organic food* (Al-Swidi et al., 2014; Činjarević et al., 2019; Lodorfos and Dennis, 2008), *moral norm* (Guido et al., 2010) and *personal norm* (Klöckner and Ohms, 2009).

The overwhelming majority of statistically positive effects with considerable versification provoke research questions about whether we can find underlying relationships from contemporary studies. Recently, the problem of *publication bias*, in which the statistical result is chosen subjectively, has been raised officially in the academy community. Thus the question is whether the positive effects are objective or subjective (Brodeur and Sangnier, 2016; C. Doucouliagos, 2005; C. Doucouliagos and Stanley, 2013). If the positive results are not biased, the next question concerns whether it can investigate sources explaining the distribution of effects of social norms on organic food adoption. The final question allows future researchers to build a better research design investigating the statistical and economic meaning of social norms (Gunby et al., 2017; Havranek et al., 2016).

In this paper, we use the meta-regression analysis to analyze the average quantified impact of social norms on the choice of organic food and then test whether there is a problem of publication bias in the research field (Brodeur and Sangnier, 2016; H. Doucouliagos and Stanley, 2009). The meta-regression analysis applies the systematic review of a sample of existing research on social norms and organic food choices. This method has proved its practical role in economics (C. Doucouliagos, 2016; H. Doucouliagos et al., 2014; Havranek et al., 2018). The method is to explore publication bias and the source for diversification of effect size (Gurevitch et al., 2018). The related meta-analysis study on organic food choice is from Scalco et al. (2017) (Scalco et al., 2017). The authors used structural equation modeling in meta-analysis for justifying the antecedents of organic food choice from *Theory of Planned Behavior*. From the study, social norms and attitudes significantly correlate with the purchasing intention of organic food, while perceived controlled behavior has a slight correlation. Our study differs from Scalco et al. (2017) in applying meta-regression analysis. We use the regression coefficient and then transform it into a partial correlation coefficient instead of Pearson's correlation. We further the research by testing for publication bias and then navigating the critical characteristics of the study relating to results. Massey et al. (2018) Massey et al., 2018 did a meta-analysis research on the determinants of purchasing organic food. The research provides a comprehensive analysis of the attributes of organic food (health benefits, quality, taste, environmentally friendly, etc.) in terms of organic food purchasing. Yet, they did not investigate the social norms in their research. Our study is complementary to the meta-analysis studies of Scalco et al. (2017) and Massey et al. (2018) by providing a meta-regression analysis on the social norms.

1.2 Methodology

1.2.1 Criteria for selecting paper

There is no restriction on the publication year of the paper. The selection criteria are (1) papers published in a journal. (2) Papers use the quantitative method and report the statistical results (coefficient, t-statistic, p-value) on the relationship between food choice and social impact (see Supplementary data Table). The meta-analysis regression uses the statistical results in each paper as an observation, so the selected papers must have the regression coefficient values of social norms, t-statistics, standard error, or p-value. If a paper does not report t-statistics, standard error, or p-value, there is a significant level for corresponding coefficients. We calculate the *p-value* by dividing the significant level by two (Stanley and Doucouliagos, H., 2012). The studies published in a journal ensure that the quality of estimation results satisfies the accepted standards.

1.2.2 Data collection

We followed the data collection from the PRISMA guideline (Moher et al., 2009). We found the papers on the Web of Science and Google Scholar. The keywords for searching are “organic food”, “consumer behaviors”, “healthy eating”, ”healthy meal”, “social impact”, “social influence”, “social norm”. Figure 1.1 shows the data collection process in the paper. We combined keywords under systematic strategies to get 134 papers, and after removing the duplication from different sources, we have 115 papers. After screening, we excluded 54 papers because they were irrelevant to our research, so we have 61 papers for full-text screening. Seventeen full-text papers did not indicate the primary relationship between social norms and organic food choice, so we excluded them. Among 44 papers for statistical values screening, we excluded the other three papers due to the lack of statistical values. Finally, we have 41 papers for meta-regression analysis.

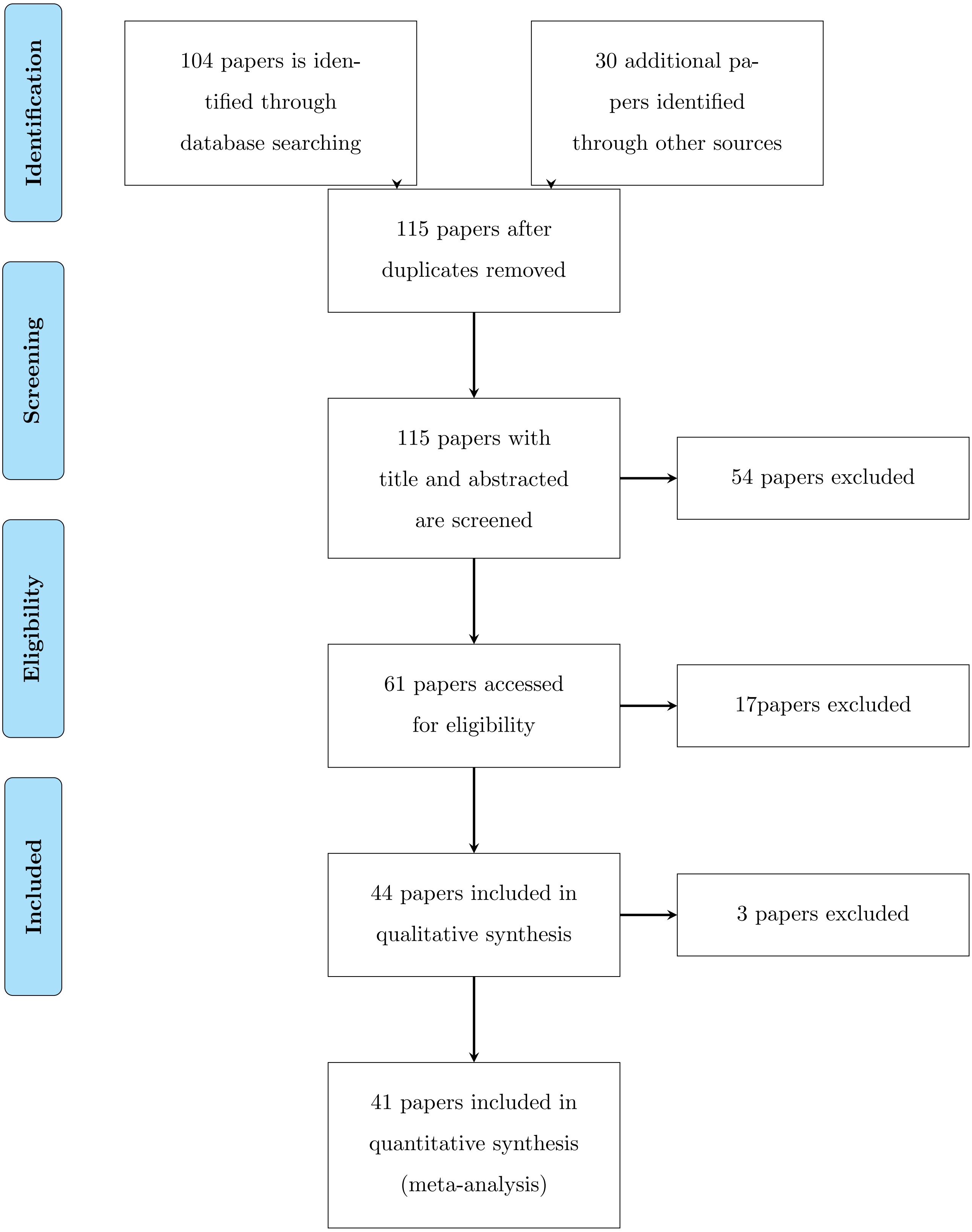

Figure 1.1: PRISMA flow chart for paper collection

1.3 Meta-regression model

1.3.1 Model without heterogeneity

The simple meta-regression model primarily establishes a verification for publication bias of reported effect sizes. The publication bias or selection bias early raised in the medical research indicates the selection of treatment results for publication (Bax and Moons, 2011). In economic and other fields, researchers could subjectively reject unfavorable results (Brodeur and Sangnier, 2016; C. Doucouliagos and Stanley, 2013; Stanley, 2005). A funnel plot and funnel-asymmetric test are standard methods to check publication bias in meta-analysis studies.

The funnel plot displays the relationship between effect size and the inverse of the standard error. In a funnel plot, where the x-axis is the effect size and the y-axis is the inverse of the standard error, there is no sign of publication bias if the plot is symmetric around the average effect size. Otherwise, the publication bias is visually assumed to exist, implying the average effect size is unreliable (C. Doucouliagos, 2016).

The funnel-asymmetric test tests the relationship between effect size and its standard error (Stanley et al., 2008). The model is:

$$b_{ij} = \alpha_0 + \alpha_1 se_{ij} + u_{ij} \tag{1.1}$$

where se_{ij} is the standard error of the effect size j in paper i; u_{ij} is the error term. A significance of α_1 supports the existence of publication bias in the effect size. Researchers in meta-regression analysis consider the value of α_0 as an estimate of average effect size (Stanley et al., 2018). However, it is argued that the estimate of α_0 in (1.1) is inflated (Stanley et al., 2018), the following proposed model replaces se_{ij} by se_{ij}^2:

$$b_{ij} = \alpha_0 + \alpha_1 se_{ij}^2 + u_{ij} \tag{1.2}$$

The model (1.2) is called precision-effect estimation with standard error (PEESE), which provides a more reliable estimate of α_0(Havranek et al., 2016; Stanley et al., 2018).

To reduce the inefficiency in the estimation of the model (1.1) and (1.2), we weight all estimations by the inverse of the variance of b_{ij}, $\frac{1}{se_{ij}^2}$ (Stanley, 2005; Stanley et al., 2018).

1.3.2 Multivariate meta-regression analysis

The model (1.1) and (1.2) are used for testing the publication bias, but they cannot explain the study heterogeneity in effect sizes (Benos and Zotou, 2014; Havranek et al., 2016). Primary studies differ in data sampling, population, research methodology, and variable choice. The inclusion of the study's characteristics in a multivariate meta-regression model helps to overcome this issue Stanley et al., 2018:

$$b_j = \alpha_0 + \sum_{i=1}^{m} \theta_i Z_{ij} + \alpha_1 se_{ij} + u_{ij} \tag{1.3}$$

where b_j is effect size j; Z_{ij} is the group of study characteristics indicated for variable explaining for effect size heterogeneity. We include the study characteristics: data collection method (self-report questionnaire, interview), data period, data origin; control variables (trust variable and health concern variable in original estimation models); journal quality (impact factor); dependent variable measurements (purchasing intention, real purchase, attitude, moral norm, personal norm). The estimation models are weighted by $\frac{1}{se_{ij}^2}$. Such a model can be specified as follows.

$$\frac{b_i j}{se_{ij}^2} = \frac{\alpha_0}{se_{ij}^2} + \frac{1}{se_{ij}^2} \sum_{i=1}^{m} \theta_i Z_{ij} + \frac{\alpha_1}{se_{ij}} + v_{ij} \tag{1.4}$$

Partial correlation coefficient

Meta-analysis requires that the effect sizes from different papers are comparable (Gunby et al., 2017). As the measurement of social norms is not identical among the studies, we use *partial coefficient correlation* calculated from the regression coefficients of the existing studies (C. Doucouliagos, 2005; Havranek et al., 2016):

$$pcc_{ij} = \frac{t_{ij}}{\sqrt{t_{ij}^2 + df_{ij}}} \tag{1.5}$$

where pcc_{ij}, t_{ij} and df_{ij} are *partial coefficient correlation* (PCC), *t-statistic* and *degree of freedom* of effect size j in paper i, respectively. The standard error is calculated as (Gunby et al., 2017; Havranek et al., 2016):

$$Se(pcc)_{ij} = \sqrt{\frac{1 - pcc_{ij}^2}{df_{ij}}} \tag{1.6}$$

The multivariate meta-regression model is as

$$\frac{pcc}{Se(pcc)_{ij}} = \alpha_1 + \frac{\alpha_0}{Se(pcc)_{ij}} + \frac{1}{Se(pcc)_{ij}} \sum_{i=1}^{m} \theta_i Z_{ij} + e_{ij} \tag{1.7}$$

The sign of PCC is the same as the sign of the effect size. PCC has the advantage (compared to the effect size) that it is non-dimensional, so different measurements of social norms are comparable.

Model selection

Including all variables Z in estimation does not guarantee the best model if all variables are considered equally important (Havranek et al., 2016, 2018; Stanley et al., 2018), so we use two empirical and common approaches for model selection: (1) General-to-specific and (2) Bayesian moving average (BMA). For the general-to-specific approach, we initially run the model with all variables and omit statistically insignificant variables whose p-value is the highest, and then a new model is run. The process is repeated until we obtain a model with all significant statistical coefficients (Stanley et al., 2018).

Bayesian moving average will run all the models combined from 16 variables in Table 1.1. After running, BMA provides the posterior mean of coefficients averaging from the set of models estimated in model space. BMA also provides a *posterior inclusion probability* (PIP) for each variable. If PIP is from 0.5 to 0.75, the variable is weak in the model. The PIP in the interval $[0.75, 0.95]$ is substantial and robust, and the probability is higher than 0.95. From the statistical software, we can obtain the results of BMA quickly and reliably, yet the BMA practice requires that the researcher states the prior belief on model size and coefficients (Havranek et al., 2016). The common practice is to have the same prior for all the possible models, so the models follow *uniform model prior*, the expected model size for K variables is $\sum_{k=0}^{K} \binom{K}{k} k 2^{-K} = \frac{K}{2}$ (Zeugner and Feldkircher, 2015):

The prior belief states that variable coefficients have a distribution with mean 0 and its variance inversely related to Zellner's g-prior (Havranek et al., 2016). There are many methods for calculating g-prior. It shows that the *Uniform Information Prior (UIP)* method, which assigns $g = \textit{sample size}$ proved to be more productive when combined with *uniform model prior* (Eicher et al., 2011; Zeugner and Feldkircher, 2015). Based on the results of BMA, we infer the average value of variable coefficients calculated by taking the mean of coefficients from all models (the coefficient of an excluded variable is zero).

Table 1.1: Description for variables in model with heterogeneity

Variable	Definition	Mean
pcc	partial correlation coefficient between social norm and organic food choice	0.158
Se_{PCC}	partial coefficient correlation' standard error in the paper	0.062
Social norms		
subnorm	= 1, if the subjective norm is used in papers, otherwise = 0	0.94
injnorm	= 1, if injunctive norm is used in papers, otherwise = 0	0.04
desnorm	= 1, if the descriptive norm is used in papers, otherwise = 0	0.02
Organic food choice		
pi	= 1, if the purchasing intention is used as organic food choice, otherwise = 0	0.770
Organic food type		
allOrg	= 1, if the paper mentions all types of organic food, otherwise = 0	0.549
fresh	= 1, if the paper mentions only fresh organic food, otherwise = 0	0.311
Analysis model		
interaction	= 1, if there is interaction relation in papers, otherwise = 0	0.164
indirect	= 1, if there is indirect relation in papers, otherwise = 0	0.107
trust	= 1, if there is variable about *trust* is included in model, otherwise = 0	0.287
health	= 1, if there is variable about *health concern* is included in model, otherwise = 0	0.344
sem	= 1, if the paper uses the structural equation modeling for estimation, otherwise = 0	0.738
Sampling		
face	= 1, if data is collected by interviewing, otherwise = 0	0.361
samRd	= 1, if the probability sampling method is applied in the model, otherwise = 0	0.618
developed	= 1, if data is from the developed countries, otherwise = 0	0.6639
obs	sample size in the paper	483.3
Publication characteristics		
impfact	impact factor of journal	2.153
year	publication year of paper	2012

1.4 Results

1.4.1 Effect size and Partial correlation coefficient

Figure 1.2 illustrates the study's forest plot of effect sizes. The plot presents the distribution of effect sizes of social norm variables in the studies on organic food purchasing in the horizontal line. The average effect size is 0.17, with a 95 % confidence interval [-0.12; 0.21]. The between-study variance τ^2 is 0.018, $p_{value} < 0.01$; thus, heterogeneity exists among the studies. The use of the random effect model is appropriate to account for the between-study variance (Nguyen-Van et al., 2021)[1].

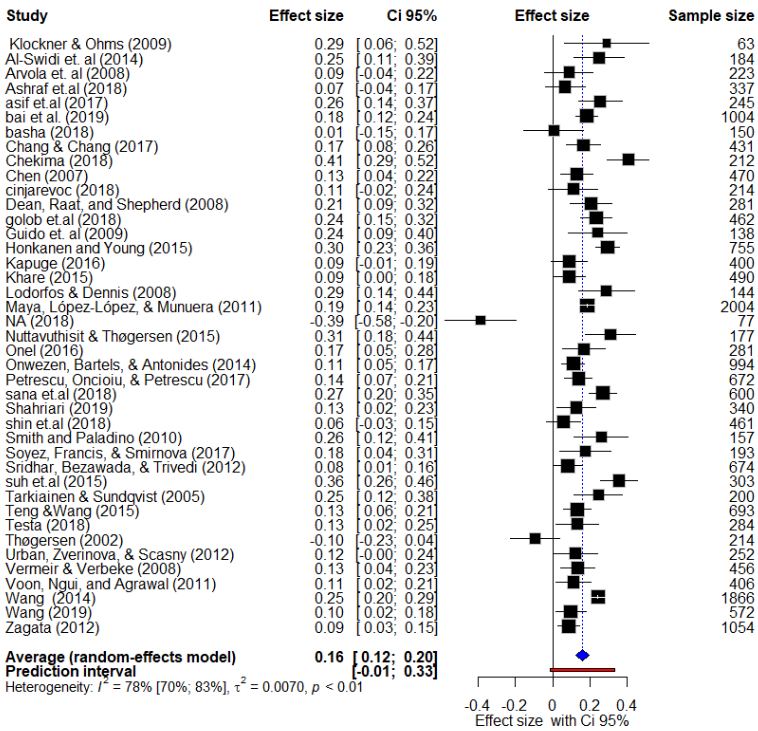

Figure 1.2: Forest plot of social norm effect on the decision of organic food purchasing

Table 1.2 shows the estimates of the random effect model above. The average partial coefficient correlations between organic food choice and social norms are around 0.16 in

[1] The model is presented as $PCC_{ij} = \beta + \xi_i + e_{ij}$ where ξ_i presents study characteristics. The regression is weighted by $\frac{1}{v_{ij}+\tau^2}$, where τ^2 is between-study variance and v_{ij} is within-study variance.

the models. Using the guideline of Doucouliagos (2011) (H. Doucouliagos, 2011), the economic relationship between social norms and organic food adoption is moderate. The similarity between fixed and random-effect models is from the small estimated value of τ^2, just 0.0049. However, the tests for heterogeneity *Q-statistic* support the existence of between-study variance. We cannot support the hypothesis that the underlying effect size in each study is the same, so it is reasonable to consider the weights that include the τ^2.

Table 1.2: The weighted average effect size

	Weight: estimate level	Weight: study level
	(1)	(4)
	RE	RE
Average effect size	0.1579	0.1568
Confident interval	[0.1231; 0.1926]	[0.1304; 0.1831]
Prediction interval	[0.0122; 0.3036]	[0.0128; 0.3007]
Between study variance indicators		
I^2	69.19%	69.19%
τ^2	0.0049	0.0049
Heterogeneity statistic Q	392.7828	392.7828
	(p ¡ 0.001)	(p ¡ 0.001)
Number of study	41	41
Number of observation	122	122

Note: *Column (1) is the average effect sizes weighted by the inverse of the variance. Column (2) shows the average size weighted by the product of variance and number of estimates per study. All the models are estimated using a cluster robust standard error method.*

The I^2 in partial correlation coefficient estimation is around 70%; this confirms that the variance of observed effect sizes is still explained by between-studies variance even if all the within-study variance approach to zero (Borenstein et al., 2017). However, I^2 positively correlates with the study's sample size and cannot convey the magnitude of effect sizes from different samples. The prediction intervals of average effect size provide a better picture of the distribution of effect sizes (Borenstein et al., 2017). The prediction interval of the partial correlation coefficient with 95% confident level is from 0.0181 to 0.2977 in the first weighting set and from 0.0178 to 0.2957 in the second one, so there exist confidently positive relationships between social norms and organic food choice when drawing different populations al. However, correlation varies from small or low to zero to moderate values. There are two other points from the intervals that require justification. Firstly, we must clarify the reasons for the widespread of the estimates. Secondly, the effect size estimates may be biased because the publication bias problem distorts the observed effect sizes (Stanley and Doucouliagos, H., 2012). We investigate that problem in the following findings.

1.4.2 Meta-regression analysis

Without heterogeneity

Figure 1.3 plots the distribution of the partial correlation coefficient with the inverse of standard errors. The black line shows the average value calculated in Table 1.2. The publication bias problem arises when the points are asymmetrical around the estimated average value (Havranek et al., 2018). The plot with publication bias will be widely spread with the decrease in the inverse of standard error if selection problems exist. From our plot, some points spread widely at the bottom-left area, but they distribute within the 95 percent confidence intervals of the estimate. From the graph, there is no strong signal of asymmetry distribution.

We test the statistical relationship between the partial correlation coefficient and its standard error by estimating the model in equation 1.1. We use the weighted least square with two weighting schemes: (1) the inverse of variance as the weight and (2) the inverse product of variance and number of estimates per study (Gunby et al., 2017; Havranek et al., 2018).

Table 1.3 shows the results for the funnel asymmetric test. The regression coefficients of standard errors are all statistically insignificant, suggesting that the publication bias

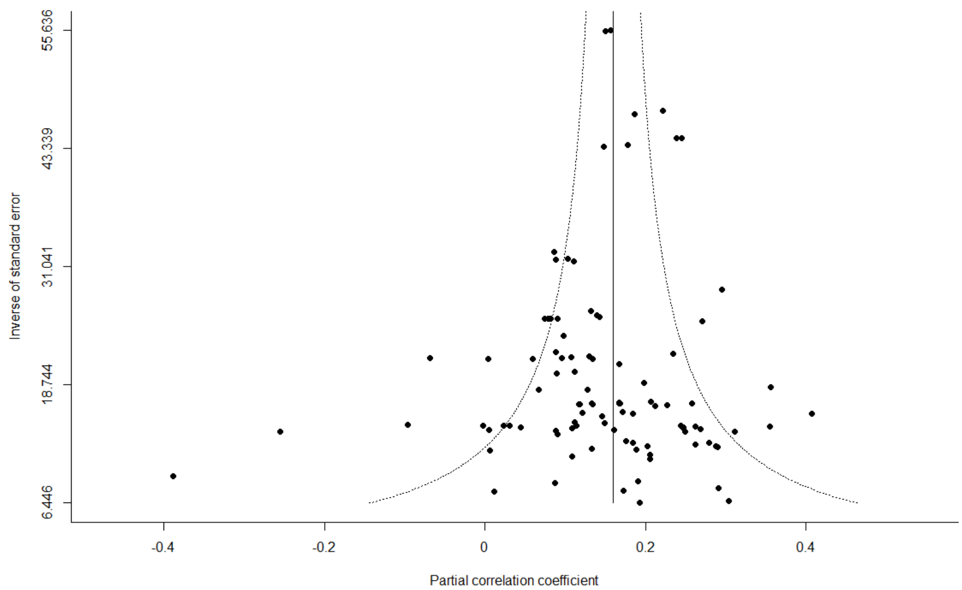

Figure 1.3: Funnel plot for partial correlation coefficient

Table 1.3: Funnel asymmetric test for publication bias

	Dependent variable: Partial correlation coefficient					
	Weight: estimate level			Weight: study level		
	WLS	FE	RE	WLS	FE	RE
Standard error	0.079	−0.849	−0.281	−0.134	−0.750	−0.237
	(0.427)	(1.146)	(0.539)	(0.470)	(1.432)	(0.561)
Intercept	0.154***		0.170***	0.164***		0.170***
	(0.025)		(0.031)	(0.027)		(0.031)
Observations	122	122	122	122	122	122

Note: The values in the bracket are robust standard errors. Column (2) to column (4) estimate using the inverse of variance as the weight. Column (5) to column (7) estimate using the inverse product of variance and number of estimates per study. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

problem does not exist in our data. The intercepts are significant in four models, indicating that the average effect size is positive, with a range of 0.154 to 0.17. We estimate the model in equation (1.2) using the partial correlation coefficient. Results reported in Table 1.4 also confirm that publication bias does not exist.

Table 1.4: PEESE rerults

	Partial correlation coefficient					
	Weight: estimate level			Weight: study level		
	WLS	FE	RE	WLS	FE	RE
Standard error	0.662	−1.945	−1.716	0.993	−1.339	−1.839
	(3.222)	(5.617)	(3.772)	(3.539)	(6.916)	(4.137)
Intercept	0.156***		0.161***	0.160***		0.164***
	(0.015)		(0.017)	(0.015)		(0.016)
Observations	122	122	122	122	122	122

Note: The values in the bracket are robust standard errors. Column (2) to column (4) estimate using the inverse of variance as the weight. Column (5) to column (7) estimate using the inverse product of variance and number of estimates per study. *p<0.1; **p<0.05; ***p<0.01.

Note that the coefficients of the intercept in Table 1.4 corresponds to the average partial correlation coefficient, which is also called precision-effect estimation with standard error (PEESE) (Havranek et al., 2016; Stanley and Doucouliagos, 2014; Stanley et al., 2018). Its range is from 0.156 to 0.164, consistent with our estimates in Table 1.3. Based on those values, we can state that the relationship between social norms and organic food choice is moderate (H. Doucouliagos, 2011).

With heterogeneity

In Table 1.5, the standard error estimates are statistically insignificant in all models, and the results from BMA are also consistent. Thus, we obtain that publication bias is not present in our data in research areas. This result is consistent with the FAT-PET-PEESE in the previous section.

The use of *subjective norm* in the primary papers has a positive relation on the value of partial correlation coefficient in Table 1.5. The results confirm that peers' opinions influence individual behavior on organic food choices. The approval and disapproval of peers are a guidance and information source for green behaviors when people tend to conform to their group (Hornik et al., 1995).

Table 1.5: Results from multivariate meta-regression analysis

	Dependent variable: Partial correlation coefficient						
	General to specific: Without study weight		General to specific: With study weight		Bayesian moving average		
	Fixed-effects	Random-effects	Fixed-effects	Random-effects	Post mean	PIP	Sign
Standard error					−0.258	−0.097	0.085
					(0.503)		
Social norms							
Subjective norm	0.053***	0.063***	0.075***	0.069***	0.055	0.197	1.000
	(0.020)	(0.019)	(0.021)	(0.024)	(0.04)		
Organic food choice							
Purchase intention					0.021	0.129	0.810
					(0.036)		
Organic food type							
All organic type					−0.039	0.254	0.014
					(0.027)		
Fresh organic food					−0.007	0.094	0.519
					(0.031)		
Analysis model							
Interaction					0.0398	0.196	0.999
					(0.029)		
Indirect			0.056*	0.065**	0.063	0.302	1.000
			(0.030)	(0.026)	(0.036)		
Trust					−0.014	0.106	0.176
					(0.03)		
Health concern		−0.033**	−0.048***	−0.036*	−0.040	0.287	0.000
		(0.016)	(0.016)	(0.019)	(0.024)		
SEM	0.079***	0.063***			0.068	0.819	1.000
	(0.016)	(0.019)			(0.024)		
Sampling							
Interview			−0.036*		0.013	0.105	0.906
			(0.021)		(0.023)		
Random sampling	0.033**				0.024	0.148	0.965
	(0.015)				(0.025)		
Developed country					−0.001	0.092	0.446
					(0.024)		
Sample size					0.088	0.001	0.722
					(0.014)		
Publication characteristics							
Impact factor	−0.028***	−0.020**	−0.033***	−0.029***	−0.021	0.835	0.000
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)		
Published year					0.000	0.113	0.282
					(0.003)		
Constant	0.091***	0.108***	0.184***	0.160***	0.352	1.000	
	(0.020)	(0.023)	(0.019)	(0.021)	(0.503)		
Observations	118	122	122	122	122		
R^2	0.253	0.179	0.321	0.216			
Adjusted R^2	0.226	0.151	0.292	0.189			
Residual Std. Error	1.577 (df = 113)	1.021 (df = 117)	0.925 (df = 116)	0.589 (df = 117)			
F Statistic	9.544*** (df = 4; 113)	6.364*** (df = 4; 117)	10.964*** (df = 5; 116)	8.068*** (df = 4; 117)			

Note: The models in columns (1) and (2) are weighted by inversion of variance of effect size in fixed-effects models and by inversion of the sum of variance and τ^2 in random-effects models. The models in columns (3) and (4) are weighted as $w^*_{ij} = \frac{1}{k_i} w_{ij}$, where k_i is the number of effect sizes in a primary paper i. The numbers in the bracket are standard errors.

All standard errors in columns (1), (2), (3), and (4) are bootstrapping standard errors.

*p<0.1; **p<0.05; ***p<0.01.

Relating to the analysis design, papers that include the *health concern* variable in organic food choice show a slight decrease in the effect sizes. The results are statistically significant in both weighting schemes, except for the fixed-effects model). The negative relationship between effect size and health concern addresses the considerable role of health concern in the choice of organic food in the sense that individuals who care about the health benefits of organic food tend to consume those foods even in the case that the social norm does not favor for this choice of consumption. Besides the social norm, consumers pay attention to the health benefits for making decisions (Khare, 2015; Klöckner and Ohms, 2009), reducing the degree of social norm in the analysis model of primary papers. The inclusion of *indirect relationship* between subjective norm and organic food adoption shows a positive relationship on effect sizes in weighting with study weights. Still, they are not statistically significant in weighting without study weights.

The sampling methodology does not show noticeable results in explaining study heterogeneity. The use of *structural equation modeling* relates to larger effect sizes in the models weighted without study weights. The *face-to-face interview* has a negative relationship to the effect size, but the result is only statistically significant in the fixed-effect model with study weights included. The randomly chosen sample may respond to a higher effect size under the fixed-effect model without study weights included. For the publication characteristics, the *impact factor* estimates, an indicator for the journal's quality, are significant in all models. The results show that the papers of high journal quality negatively relate to effect sizes.

1.5 Discussion and conclusion

Firstly, the results do not support the existence of publication bias in research areas; these findings consist of those from Bax and Moons (2011). The estimated effect sizes from the meta-analysis are more reliable in concluding that there is a moderate-positive relationship between social norms and organic food adoption. The factors that influence the behavior of consumers toward organic food are the views, opinions, and behavior of other people (Aertsens, Verbeke, Mondelaers, and Van Huylenbroeck, 2009a; Ajzen, 1991), so the researchers or policymakers can build appropriate tools for creating the incentives for the adoption of organic food.

Secondly, subjective norms have more influence on consumers' behavior than descriptive norms. This indicates that the pressure from other's opinions is higher than the observed behavior from others (Povey et al., 2000). A policy encouraging organic food may be inefficient if it does not pay sufficient attention to create an opinion trend among consumers (Goldstein et al., 2008). However, the descriptive norm should be used with subjective or injunctive norms to provide more efficient results in changing the pro-social behavior (Cialdini et al., 2006), mainly organic food choice.

Thirdly, the *health concern* toward food consumption is an essential determinant in organic food choice. People have a positive perspective on organic food's health benefits, which incentivizes buying the products (Khare, 2015; Klöckner and Ohms, 2009). The primary papers that included the health indicators in the models provided less partial correlation coefficient between social norms and organic food choice.

The effect size range is extensive because of each study's characteristics, as indicated in Table 1.2. Our analysis suggests that using *structural equation modeling* and the *random sampling* have statistical explanations for the study heterogeneity in effect size between primary papers. The *quality of journal*, indicated by impact factor, also shows a negative relationship with the effect size. Thus, future research should focus on the choice of research design for their effect size.

Finally, adopting organic food provides positive consequences for food safety and a sustainable environment. Both theoretical models and empirical research support the role of social norms in organic food choices. Our study applied the meta-regression analysis to investigate that role again, and we concluded that there is a positive relationship between social norms and organic food adoption. The result pays more for future policies implementing social influences to incentivize consumers.

Chapter 2

Farmers' preferences toward organic certification scheme: Evidence from a discrete choice experiment in Northern Vietnam

This Chapter is an updated version of a chapter in the thesis "Incitations individuelles et comportements pro-environnementaux : le rôle des réseaux" of TUYEN TONG TIET, defended on 15/12/2020 at Strasbourg. The corresponding thesis could be found at https://theses.fr/2020STRAB013

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Summary

This study uses a quantitative approach based on a discrete choice experiment with 586 farmers in Northern Vietnam to measure how representative market and non-market factors could influence their preferences for participating in organic certification schemes. Our results suggest that a sales contract with flexible or guaranteed prices is a significant incentive to explain their willingness to pay higher production costs to be involved in organic certification schemes. Furthermore, providing farmers with training and technical support is also essential to motivate farmers toward organic agriculture. Finally, neighborhood cooperatives and formal leaders' participation in organic farming could encourage farmers to convert to organic agriculture.

Keywords*: Discrete choice experiment; Organic certification; Farmers' preferences; Leadership; Role of network.*

JEL Classification*: C93; D10; Q00.*

2.1 Introduction

For decades, a rapid expansion of global agriculture has seriously threatened worldwide biodiversity (Dudley and Alexander, 2017; Zabel et al., 2019). Particularly, intensive food production poses significant threats to the environment, such as pollution from pesticides and fertilizers, greenhouse gas emissions, and loss of biodiversity from the conversion of vast amounts of natural ecosystems into croplands (Tilman and Clark, 2015; Tilman et al., 2002). Moreover, a conventional farming system that heavily relies on chemical inputs (e.g., pesticides and chemical fertilizers) is associated with severe environmental and health problems (e.g., extreme soil, water, and crop pollution) (Bengtsson et al., 2005; Zhengfei et al., 2005). For instance, according to the Intergovernmental Panel on Climate Change (IPCC), conventional agriculture accounts for one-fifth of the greenhouse effect leading to global climate change (Masson-Delmotte et al., 2018).

Organic agriculture is proposed as a solution to prevent environmental degradation (e.g., preserve soil fertility in the long term) by producing foods that are less dependent on fertilizers and chemicals (Cui et al., 2018; Liu et al., 2016). Specifically, organic farming could enhance food safety, increase employment opportunities, reduce external input costs, and improve farmers' income (Jouzi et al., 2017; Reganold and Wachter, 2016). However, besides its wide range of environmental advantages, organic yields are significantly lower than modern agriculture's, thus lowering its contribution to global food security (Borghino et al., 2024; De Ponti et al., 2012). Despite its low contribution to global food security, organic farming has continued to expand worldwide. For instance, in recent years, organic farming has been encompassing 11.7 million hectares of organic farmland worldwide (i.e., about 20% of agricultural land) in 2017.[1]

The sizeable organic market opens various opportunities for producer countries to produce organic products and gain high profits. According to the FiBL-IFOAM survey in 2019, there were around 6.1 million hectares of organic agricultural land in Asia in 2017, accounting for 9% of the world's organic agricultural land. Of this number, China and India are leading countries by organic agricultural land with 3 million hectares and

[1] The complete report is available at https://shop.fibl.org/CHfr/mwdownloads/download/link/id/1202/?ref=1

1.8 million hectares, respectively (Willer and Lernoud, 2019). The organic agricultural product market also gradually developed in Vietnam, with 10,150 organic producers and 58,018 hectares devoted to organic agriculture in 2017 (Willer and Lernoud, 2019). However, it accounts for only 0.5% of total agricultural land, even though Vietnam is one of the largest agricultural producers in Asia, and it has succeeded in managing its agricultural sector in the last two decades, particularly for rice (Lakitan, 2019). Thus, examining the growth and trend of organic farming in Vietnam is essential.

Several developing countries like Vietnam are currently in a start-up phase that requires strong support in their agricultural sector. For instance, a large proportion of land in Vietnam is dedicated to agriculture (around 0%). At the same time, a majority of farmers are smallholders (i.e., about 89%) who mainly live in rural areas, and their primary income sources have come from agricultural products (Rapsomanikis, 2015). However, in their study, the authors argued that Vietnamese farmers rely heavily on farming inputs, such as pesticides, fertilizers, and crop protection (Rapsomanikis, 2015). This result is also one of the reasons why organic farming land accounted for only about 0.5% of total agricultural land in Vietnam in 2017 (Willer and Lernoud, 2019).

The existing literature has suggested that farmers' decisions to adopt organic farming are influenced by various market and political factors, such as agricultural policy, market configuration, and technology design (Darnhofer et al., 2005; Jaime et al., 2016; Schneeberger et al., 2002). Several studies suggested that market barriers, such as a slow expansion of the market for organic products and a lack of certification system, need to be overcome to boost organic farming conversion (Schneeberger et al., 2002). Sufficient information about the benefits and standards of organic products could decrease marketing costs and thus reduce the price of organic products (Soltani et al., 2014). Therefore, organic certification schemes could help ensure certified farmers with a stable income from a higher opportunity to access new markets with a guaranteed product price premium (Sapbamrer and Thammachai, 2021).

In addition to the market and non-market factors associated with organic certification schemes, such as certification, logo, training, and guaranteed price, farmers' networks are an essential motive for organic farming conversion. More specifically, a network is a valuable source of information for farmers to exchange information and spread social preferences since most farmers always belong to a local network, such as a network of neighborhood farmers, friends, or agricultural organizations in the local area (e.g., farmers' association or cooperative) (Maertens, 2017; Nguyen-Anh et al., 2022). Several studies have suggested that farmers are more likely to acquire information about dairy farming within their interpersonal social network, which could enhance their learning and productivity (Hoang-Khac et al., 2021; Sligo and Massey, 2007). Some other studies argued that frequently communicating/discussing with other neighborhood farmers could significantly promote the adoption of organic farming(Läpple and Van Rensburg, 2011; Unay Gailhard et al., 2015).

While most of these studies focused on farmers' willingness to accept (WTA) changes in revenue and incentive payments to convert to organic farming, there is a handful of evidence on farmers' willingness to pay (WTP) changes in production cost to involve in organic certification schemes and the role of the network (e.g., adoption decisions of neighborhood farmers and leaders in the local villages) on farmers' preferences toward organic farming. Several studies examined the critical role of organic certification schemes in encountering an increasing consumer interest, signaling their environmentally friendly products, differentiating between competing in the competitive market, and getting access to new markets that ensure guaranteed product price (Albersmeier et al., 2009; Altobelli et al., 2019; Tran et al., 2022).

However, a handful of evidence assesses the role of non-market attributes, especially the role of networks and participation of leaders, on farmers' WTP/WTA in the adoption of organic certification. Thus, we contribute by filling this gap and assessing farmers' preferences and willingness to pay changes in production cost to be involved in organic certification schemes using a discrete choice experiment. In particular, we aim to provide insight into farmers' preferences for a hypothetical organic certification scheme based on various market attributes (i.e., sales contracts and logos with traceable codes), non-market attributes (i.e., the role of networks, participation of leaders, training and technical assistance) and estimate their economic value in terms of marginal WTP.

The remainder of the paper is structured as follows: Section 2 explains the study's background and the literature review. Section 3 summarizes our choice of experimental design, data collection, and the main characteristics of the farmers interviewed. Section 4 describes the econometric model. Section 5 discusses the main estimation results, and Section 6 provides a discussion and conclusion.

2.2 Background and literature review

2.2.1 Organic farming in Vietnam

Organic agriculture originated as a critique of the expanding industrial food system between the 1920s and 1950s (Barton, 2018; Lotter, 2003). Until the 1980s, organic agriculture, which promised a more 'natural' and healthier agriculture, has been experiencing a surge in popularity due to emerging environmentalism and health concerns about exposure to pesticides, antibiotics, and hormones (Lotter, 2003). In the United States (US), the first state-level organic rules appeared in the 1970s, followed by the National Organic Program (NOP) approximately 30 years later (Mosier, 2017; Youngberg and DeMuth, 2013). The first European-wide organic rule was formed in 1991, replacing national regulations in most countries since the 1980s (Stolze and Lampkin, 2009). Some nations, such as Australia, do not yet have a legally enforceable national organic regulation but instead rely on broadly recognized national voluntary standards established by government authorities or the organic industry (Seufert et al., 2017).

At the international level, various organizations strive to standardize organic standards worldwide. The International Federation of Organic Agriculture Movement (IFOAM), an umbrella organization founded in 1972, and the Codex Alimentarius, established in 2001 by the Food and Agriculture Organization (FAO) and the World Health Organization (WHO), aim to develop a consensus definition of organic practices across different countries, allowing for free trade in nationally regulated organic food and thus significantly impact the development of several national organic standards (Organization, 2001). Many developing countries have recently implemented organic legislation to facilitate trade with high-income countries (Unnevehr, 2022). Uganda, for example, implemented a national organic standard in 2004, followed by a regional East African organic standard in 2007 (Namuwoza and Tushemerirwe, 2011). Similarly, after seeing significant expansion in the organic industry, Mexico established a national organic program in 2006 and a national organic standard with production requirements in 2013 (Rosina Bara et al., 2018). Currently, approximately 100 countries worldwide have adopted or are implementing organic standards.

In Vietnam, research on organic agriculture is attracting researchers' attention. There are five common Sustainable Agricultural Practices (SAPs) applied in Vietnam: "Crop rotation" (i.e., growing different types of annual or biannual crops on the same land in sequential seasons), "Intercropping" (i.e., cultivating two or more crops on the same plot at the same time), "Soil and water conservation practices" (i.e., activities at the local level that maintain or enhance the productive capacity of the land in areas affected by degradation), "Organic fertilizers" (i.e., application of agricultural waste residues as effective alternatives to chemical fertilizers) and "Leaving the land fallow" (i.e., restoring soil fertility and nutrients, re-establishing soil biota, breaking crop pest and disease cycles as well as providing a haven for wildlife)(H.-G. Pham et al., 2021). SAPs help farmers reduce the appearance of pests and diseases and maintain productivity despite harsh conditions from climate change, thus improving yields and household income. However, adoption of SAPs is still low in developing countries, particularly Vietnam.

Some studies suggested a low adoption rate of organic farming is due to weaknesses in policy implications, unreliable certification processes, and the distrust of consumers (V. H. Pham et al., 2009; Thai et al., 2017). For instance, Vietnamese consumers are unfamiliar with organic food labels and certification because there was no official national certification or designation for organic products until recent years (N. H. My et al., 2017). The Vietnamese government has encountered difficulties managing and regulating those pesticide practices (Van Hoi et al., 2013). Some studies have indicated that Integrated Pest Management (IPM) helps regulate the use and management of insect pesticides and reduce the use of pesticide inputs (Berg, 2002). However, IPM has been evaluated as unsuccessful in Vietnam (Hoi et al., 2016). For instance, Vietnamese farmers do not follow the correct practices required for pesticides and fertilizers in the field (Toan et al.,

2013).

Moreover, most Vietnamese farmers are involved in a conventional farming scheme, in which they highly depend on the use of chemical pesticides and fertilizers to have higher yields and profits from farming since synthetic substances are easy to use and require low labor inputs (Berg, 2002; Richter et al., 2015). However, the consequences of artificial substances (e.g., pesticide overuse) tend to increase insect resistance and, therefore, lead to severe impacts on the health of both farmers and consumers in the long run (Berg and Tam, 2018; World Bank, 2016). For instance, pesticides cause severe chemical contamination in soil and surface water, especially "ready-to-drink" sources, and thus, people living in the surrounding area are at a health risk of consuming polluted water, especially Vietnamese farmers (Richter et al., 2015; Thai et al., 2017; Toan et al., 2013). Therefore, it is essential to encourage farmers to shift toward sustainable agriculture by providing information via training or sharing experiences with farmers to improve environmental quality and public health (Dinh et al., 2023; Sapbamrer and Thammachai, 2021; Tran-Nam and Tiet, 2022).

2.2.2 Discrete choice experiment and organic farming

The discrete choice experiment (DCE) is based on repeated individual choices among hypothetical scenarios differentiated by attributes and status quo scenarios. The DCE is commonly used to calculate the WTP or WTA to participate in some agricultural schemes (Kwanmuang et al., 2018; Schulz et al., 2014) and to determine how different attributes influence farmers' adoption of new technology (Espinosa-Goded et al., 2010; Jaeck and Lifran, 2014; Kwanmuang et al., 2018). Existing literature has argued that adopting organic farming requires farmers to change their habits by limiting the use of pesticides and fertilizers. From a farmer's perspective, reducing pesticides and fertilizers could increase the risk of productivity loss (Chèze et al., 2020a). Therefore, farmers willing to adopt an organic farming scheme require a guarantee to compensate for this risk.

Several studies have suggested that farmers are often uncertain about markets for and the prices of organic products (Jaeck and Lifran, 2014; Van den Broeck et al., 2017). Sales contracts for organic foods (with either flexible or fixed prices) are a solution to overcome the uncertainty of adopting organic agriculture (Greiner, 2016). Payment for the agri-environmental scheme is also a significant barrier to farmers' uptake of environmental programs (Greiner, 2016; Villanueva et al., 2015). Farmers often have information about the cost of conventional farming but are uncertain about the cost of organic agr culture. Farmers' decisions to adopt organic farming are not only limited by economic factors but also by non-economic factors. The influence of social acceptance on farmers' adoption of organic agriculture is essential and needs to be considered (Daxini et al., 2018). In their study, the authors found that Irish farmers observe other farmers' behaviors and then consider adopting organic farming or not (Läpple and Kelley, 2013). Based on the Theory of Planned Behavior(Ajzen, 1991), behavioral change depends partly on the farmer's understanding. Knowledge and know-how are also necessary for them to make their choice. Moreover, farmers need information and training to grow organic vegetables Adebayo and Oladele, 2013. Without accurate information and knowledge of organic farming, there can be resistance to adoption (Bessette et al., 2019). In the model of new technology adoption, temporal issues can play a role in the sense that some farmers will adopt earlier than others. These farmers are referred to as "opinion leaders". Opinion leaders influence their followers by providing information about the quality of adoption (Padel, 2001).

In addition to these crucial determinants, farmers' socio-demographic characteristics, the size of the farm (i.e., large-scale or smallholder farmers), and farmers' attitudes toward the environment can also help to explain farmers' decisions to adopt organic agriculture (Darnhofer et al., 2005; Läpple and Van Rensburg, 2011; Padel, 2001; Pilarova et al., 2018). In the study of the determinants of sustainable agriculture adoption in Moldova, the authors concluded that farmers' household characteristics (e.g., age, number of children, number of adults, etc.) and farm size are important factors influencing farmers to adopt sustainable agriculture (Pilarova et al., 2018). Additionally, farmers' awareness and concern about the environment and the consequences of farming activities positively impact adopting sustainable agriculture (Zeng et al., 2019).

2.3 Choice experimental design

2.3.1 Attributes

Our choice experiment was offered to respondents with multiple-choice scenarios. Given a hypothetical situation, farmers were asked to choose one of three options: two ”organic certification” alternatives (options 1 and 2) and a ”status quo” alternative in which farmers decided to choose neither organic option 1 nor 2. Several different attributes describe the two alternative ”organic certification” options.

Our study’s attributes selection is based on the literature review and discussions with experts in Vietnam. A face-to-face meeting with several experts from agricultural sectors and NGOs, including the Director of the Van Duc farming cooperative, the President of the Farmer Union of the Van Duc Commune, the President of the Agricultural Extension Association, and Specialists of the Vietnam Agricultural Sustainable Development Organization, was organized at the Van Duc Commune, Gia Lam District, Hanoi. Following the discussion, we agreed that six important attributes affect the farmers’ decisions toward organic certification: (1) Training and technical advice; (2) Sales contract; (3) Traceability; (4) Neighbor; (5) Leadership; and (6) Additional cost per kg. Each attribute contains different levels for building scenarios.

Firstly, our experiment aims to analyze farmers’ preferences for organic certification based on the first attribute, “Training and technical advice”. This attribute is defined as practical lessons delivered free of cost to farmers to improve their knowledge about organic farming and organic farming practices. In addition to the “Training” aspect, local technicians or specialists would provide technical advice farmers to help them apply the principle of organic farming. Secondly, we analyze the farmers’ sensitivity to different types of sales contracts between farmers and buyers within the context of organic agriculture based on the second attribute, “Sales contract”. The buyers may be retailers (e.g., supermarkets, companies), cooperatives, or direct consumers. Two types of contracts are proposed: a contract with fixed/guaranteed prices and a contract with flexible prices. Thirdly, the experiment also includes the attribute “Traceability”, a traceable code corresponding to an organic logo on each organic product. Traceable codes on organic products help consumers distinguish between organic and non-organic products and indicate that farmers' products have already been subjected to strict quality control. Fourthly, the attribute "Neighbors" is used to capture farmers' preferences in coordination with neighbors in doing organic farming. Fifthly, the "Leadership" attribute is the presence of formal (e.g., village leaders or president of the farmers' association) and informal (e.g., religious leaders or the most successful farmers in the village) leaders, using to estimate farmers' preferences in different levels of leaders' communal participation in organic farming. Finally, the "Cost" attribute is a central element used to capture farmers' WTPs regarding additional production costs for organic certification schemes. The cost includes six levels, defined in percentage increase in production costs: 0%, 10%, 30%, 60%, 100%, a d 150%. The additional cost per kilogram (kg) accurately captures farmers' WTPs because farmers in different areas often produce various agricultural products. Even farmers who grow the same type of products may have a wide range of production costs. Detailed information about attributes and their levels is provided in Table 2.1.

Table 2.1: Attributes, attribute levels, and experimental design in the choice experiment.

Attributes		Attribute levels
Training and technical advice		Without lessons.[1] With lessons.
Sale contract		No contract.[1] Contract with a guaranteed price. Contract with a flexible price.
Traceability		Logo without traceability.[1] Logo with traceability.
Neighbors		No neighbor producing organic.[1] Coordination with other neighbors producing organic farming.
Leadership		No leader producing organic farming.[1] Formal leader producing organic farming. Informal leader producing organic farming. Both formal and informal leaders producing organic farming.
Additional cost per unit		0%[1] / 10% / 30% / 60% / 100% / 150%.

2.3.2 Experimental design

The six attributed to different levels have 864 combinations using a full factorial design, which is unrealistic to include all alternatives in a discrete choice. Applying the NGENE software, we constructed a fractional factorial orthogonal design with 30 choice sets divided into three blocks of ten choice sets (Table 2.1); the values of attributes describing the two alternative organic options vary across every choice task. The choice experiment was conducted through face-to-face iPad-assisted interviews. In particular, respondents were invited to select their favorite farming option among three alternative options (i.e., two alternative organic options and one "status quo") across the different choice tasks. Several assistants were used during the experiment to help respondents use iPads.

Before delivering the choice card to respondents, each assistant explained the detailed definition of each attribute to the farmers. Two choice card examples were given to farmers to test their understanding of the experiment. There were ten choice cards for which respondents were invited to choose their preferred alternative. Two additional choice cards were used as examples to test the farmers' understanding of the experiment (see Figure 2.1 for an example of the choice card).[2] On each choice card, respondents had to choose the one farming option that they preferred from among two organic certification schemes and one status quo (i.e., "no change" or "I prefer the current farming situation") situation. The status quo represents the current farming situation, meaning respondents were not involved in organic certification schemes. 5,860 valid observations were collected from 586 farmers and used for the empirical analysis.

In addition to the preliminary experiments, we collected participants' information on various socio-demographic characteristics. In particular, we collected data on age, gender, farm size, household size, type of residence, individual and household income, health, level of education, marital status, number of children in the household, individual attitudes toward risks, attitudes toward the environment via New Environmental Paradigm (NEP) questionnaires, and perception of the adoption of organic farming. The detailed descriptive statistics are presented in the next section.

[2] A Vietnamese version of the choice card is reported in Figure 2.2 in Supporting Information section

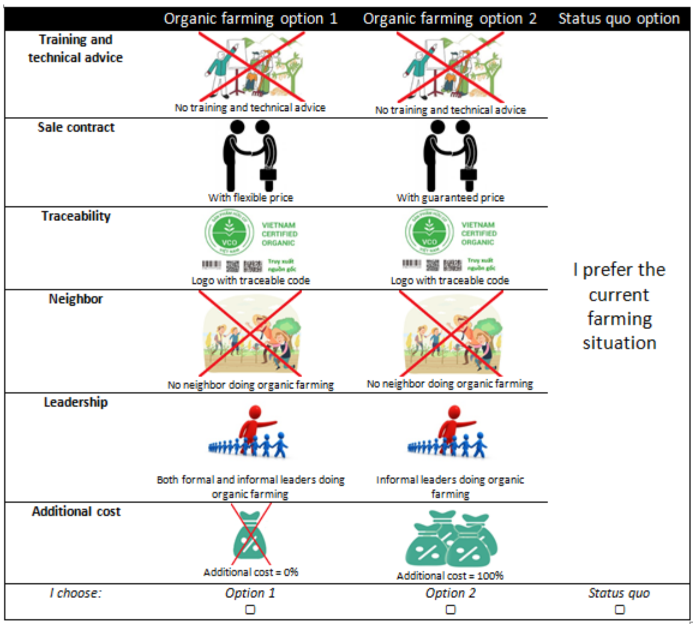

Figure 2.1: Example of choice card (in English).

2.3.3 Data

Our data were collected from a choice experiment among farmers not involved in organic farming schemes in 31 villages in Northern Vietnam. The data was collected in August 2019 in eight villages, in November 2019 in 11 villages, and from December 2019 to January 2020 in 12 villages. These 31 villages in seven provinces surrounding Hanoi were chosen because they produced the most significant number of agricultural products (vegetables, rice, and fruits), and they are Hanoi's major suppliers of agricultural products. In recent years, Hanoi has been severely impacted by food safety issues, particularly vegetables, and fruits (Ha et al., 2019; Van Hoi et al., 2009). Consequently, these agricultural-producing provinces were chosen to explore the influence of socio-psychological factors on farmers' decisions to transition to organic agr culture. Based on village-level data regarding the number of agriculturally producing households, two to three villages were selected as representatives of each province.

596 farmers participated in the choice experiment (see the map of the experimental areas in Figure 2.3 in the Supporting Information section). However, we finally obtained a total of only 586 valid survey answers. Ten invalid observations were removed from the dataset because of missing information about the respondent's production costs. The

current production cost is essential for calculating the "cost" attribute and estimating the WTP. The experiments were conducted with farmers in the village using iPads.

The experiment consisted of four different parts. The first part of the experiment included warm-up questions designed to obtain information about farmers' current farming situations and their past situations related to organic farming. The second part addressed the choice experiment, including 12 choice cards. Note that the first two choice cards were used as examples to understand the choice experiment better experiment. The third part of the experiment was designed to obtain information about farmers' production activities (e.g., primary agricultural products, production cost, etc.). The last part was to get information about farmers' socio-demographic characteristics, lifestyles, environmental attitudes, and perceptions of organic farming. In addition to farmers' socio-demographic characteristics, we also elicited information on farmers' environmental concerns via 15 NEP questionnaires (see the details of the NEP questionnaires in Table 2.6 in Supporting Information section A) (Dunlap et al., 2000). Several other questions related to environmental concerns were also asked to capture farmers' opinions, attitudes, and apprehensions toward the environment. At the end of the questionnaire is a follow-up survey to collect information on farmers who always prefer the "status quo" or "organic certification" alternatives. This follow-up survey helps us to understand these specific behaviors.

2.3.4 Descriptive statistics

The descriptive statistics of socio-economic characteristics, individuals' concerns about the environment, and their perceptions of adopting organic farming are presented in Table 2.2. The socio-economic control variables include: *Types of agricultural products* with three dummy variables ($Rice$, $Vegetables$, and $Others$) that take a value of 1 if farmers mainly produce rice, vegetables and other types of products, respectively; $Female$, a dummy that takes a value of 1 if the farmer is female; Age is the log of individual age; $Education$ is a category variable that takes the value of 1, 2 or 3 if the level of individual's education is below secondary school (grade 6 to grade 9), or below vocational school (1 to 2 years after high school), or college and university; $Health$ is a category variable that takes the value of 1, 2 or 3 if the individual has bad health, good health or very good health, respectively; $Income$ is a category variable that takes a value of 1 if the individual is in the low-income group (monthly earnings $<$ 4 million VND), a value of 2 if the individual is in the middle-income group (monthly earnings from 4 to 8 million VND) and a value of 3 if the individual is in the high-income group (monthly earnings $>$ 8 million VND); $Farmsize$ is the log of the farmer's household farm size (in m^2).

Table 2.2: Summary statistics of survey respondents (N=586)

	Mean	Std.Dev	Min	Max
Types of agricultural products				
Rice	0.45	0.49	0	1
Vegetables	0.33	0.47	0	1
Others	0.21	0.40	0	1
Production cost (VND/kg)	5,843.81	4,316.78	500	46,723
Female	0.66	0.47	0	1
Age (yrs)	51.30	11.67	18	74
Age (in log)	3.90	0.25	2.89	4.30
Education				
Secondary school	0.67	0.46	0	1
High school	0.27	0.44	0	1
College/University	0.06	0.23	0	1
Health				
Bad	0.05	0.21	0	1
Good	0.78	0.41	0	1
Very good	0.17	0.37	0	1
Individual income				
Low	0.63	0.48	0	1
Middle	0.29	0.45	0	1

High	0.07	0.25	0	1
Farm size (m^2)	4,221.17	7,035.40	50	70,000
Farm size (in log)	7.79	0.96	3.91	11.15
NEP score	47.60	4.63	35	64
Perception score	15.1	2.35	4	20

Notes: Other agricultural products include fruit, coins, and other types of products.

In addition to the socio-demographic control variables, the psychological control variables include (1) *NEP score*, the aggregate score of 15 individual NEP questions (Table 2.6 in Supporting Information section); and (2)*Perception score*, the aggregate score of four items related to farmers' perceptions of adopting organic agriculture in Table 2.7. The total NEP score is the aggregate score of 15 NEP questions, in which Cronbach's alpha is equal to 79.02%, and questions number 2, 4, 6, 8, 10, 12 and 14 (even number questions) are reversely coded (Cronbach, 1951). While the *NEP score* variable captures respondents' environmental concerns, the *Perception score* measures respondents' perceptions of adopting organic farming. This aggregate perception score is calculated using four 5-point Likert scale items (see Table 2.7).

According to the statistics reported in Table 2.2, a majority of farmers in our sample produced rice (45.39%) and vegetables (3.62%). The rest of the farmers produced fruit, corn, and other agricultural products. The average production cost for three different agricultural products was about 5,843 VND/kg.[3] Farmers were, on average, 51 years old, ranging from 18 to 74 years old. There were 66% of female farmers in our sample. Most of the farmers in the sample were smallholders with an average farm size of 4,2 1 m^2. The farmers' education level was below high school, with only 6% having graduated from college or university. About 78% of the farmers in our study indicated good health. Most farmers belonged to the low-income group since their monthly income was below 4 million VND[4]. Only 7% of farmers told us that they had an income higher than 8 million

[3]equivalent to about 0.25 USD/kg.

[4]equivalent to about 167 USD per month.

VND/month.

2.4 Econometric model

In this section, we briefly discuss how Random Parameter Logit (RPL) and Hybrid Choice Model (HCM) structures are applied to study farmers' preferences toward organic certification schemes (Anastasopoulos and Mannering, 2011; Ben-Akiva et al., 2002; Bolduc and Alvarez-Daziano, 2010; McFadden, 1973). In a standard Random Utility Model (Hensher, 1982; McFadden, 1973), we consider that the individual i's utility function for alternative n in choice task t is given by:

$$U_{i,n,t} = V_{i,n,t} + \epsilon_{i,n,t}, \tag{2.1}$$

where $V_{i,n,t}$ is the deterministic component of i for alternative n in choice task t, and $\epsilon_{i,n,t}$ is the error component (i.e., random component) of the utility function.

Let $x_{i,n,t}$ be a set of observable attributes of the alternative n and z_i be a set of respondent i's socio-economic characteristics (e.g., income, age, education, etc.). In a traditional model, we have $V_{i,n,t} = f(x_{i,n,t}, z_i, \beta)$ where $f(.)$ is a linear-in-attribute specification. The two organic certification options $V_{i,n,t}$ for $n = \{1, 2\}$ are written as follows:

$$V_{i,n,t} = \mu_{ASC} ASC_{i,n,t} + \sum_{l=1}^{L} \beta_l Attribute_{i,l,n,t} + \beta_c Cost_{i,n,t} + \sum_{s=1}^{S} \gamma_s ASC_{i,n,t} * Control_{i,s}, \tag{2.2}$$

where $ASC_{i,n,t}$ is defined as the Alternative Specific Constant (ASC) taking value 1 if the organic alternatives are chosen to capture the unobserved influences on the utility function in the unlabeled choice experiment (i.e., the two organic alternatives are unlabeled). Thus, parameter μ_{ASC} is the coefficient of the dummy variable $ASC_{i,n,t}$. The control variables $Control_s$ include a set of S socio-economic variables (e.g., farmer's characteristics, individual income, etc.). $Attribute_l$ is a set of L attributes, including "Training and technical advice", "Sale contract", "Traceability", "Neighbors", and "Leadership".

Random Parameter Logit Model

Consistent with the existing literature, we assume that the errors are independently and identically distributed with an extreme value, leading to a logistic form for the probability of choosing alternative j (Anastasopoulos and Mannering, 2011; Hynes, Hanley, et al., 2005). However, in contrast to the literature, since the unit cost was collected after the choice sets in our experiment, there are three ways to estimate the model. Firstly, we directly estimate Equation (2.2) using a conditional logit (CL) model based on $Attribute_l$ and the ASC i dicator. This regression gives estimates for $\mu_{ASC}, \beta_l, \gamma_s$. Secondly, since there could be heterogeneity in individual preferences that could influence respondents' decisions, RPL could be used to account for individuals' heterogeneity.

$$V_{i,n,t} = \mu_{ASC} ASC_{i,n,t} + \sum_{l=1}^{L} \tilde{\beta}_l Attribute_{i,l,n,t} + \beta_c Cost_{i,n,t} + \sum_{s=1}^{S} \gamma_s ASC_{i,n,t} * Control_{i,s}. \tag{2.3}$$

This corresponds to a model with parameter heterogeneity (or random parameters) associated with the attribute variables. Its estimation requires an additional assumption about this heterogeneity, i.e.

$$\tilde{\beta}_l = \bar{\beta}_l + \vartheta_l \tag{2.4}$$

where $\vartheta_l \simeq \mathcal{N}(0, \Omega)$, where Ω is the variance-covariance matrix of dimensions $K + 1$ (which is the total number of levels in the attributes). RPL regression gives estimates for $\bar{\beta}_l$, μ_{ASC} and γ_s.

Hybrid Choice Model

Respondents' decisions to be involved in organic certification schemes are also influenced by their attitudes toward the environment in Table 2.6 and perceptions of adopting organic farming in Table 2.7. Let I_i be indicators of respondent i's attitudes toward the environment and perceptions of adopting organic farming. The existing literature has indicated that the simple inclusion of I_i in $V_{i,n,t}$ is theoretically misguided because of the risk of endogeneity bias since there is likely to be a correlation between I_i and other unobserved factors $\epsilon_{i,n,t}$ influencing respondent i's behavior (Ben-Akiva et al., 2002; Bolduc and Alvarez-Daziano, 2010).

The HCM is an approach developed to deal with this problem by considering I_i as a dependent rather than an explanatory variable. In particular, the HCM model hypothesizes the actual underlying individual attitudes, concerns, and perceptions could be described as a set of k unobserved latent variables, namely $V_{i,k}$. These latent variables (LVs) could influence the respondents' answers to the attitudinal and perceptional questions and thus drive their behaviors in the actual choice situations. More specifically, the latent variables for respondent i (i.e., the structural equation for latent variables) are given by:

$$LV_{i,k} = \sum_{s}^{S} \gamma_{LV_k,s} z_{i,s} + \xi_{i,k}, \tag{2.5}$$

where $z_{i,s}$ is a set of S socio-demographic variables of respondent i (e.g., age, gender, income, etc.), γ_{LV_k} is the k vector of estimated parameters capturing the impacts of socio-demographic variables on $LV_{i,k}$ and $\xi_k \simeq \mathcal{N}(0,1)$ is a random disturbance that follows a standard normal distribution across individuals.

The utility specification where the latent variables are incorporated (i.e., choice model components) is expressed as follows:

$$\begin{aligned} V_{i,n,t} = {} & (\mu_{ASC} + \lambda_{NEP} LV_{i,NEP} + \lambda_{Perception} LV_{i,Perception}) ASC_{i,n,t} \\ & + \sum_{l=1}^{L} \beta_l Attribute_{i,l,n,t} + \beta_c Cost_{i,n,t} + \sum_{s=1}^{S} \gamma_s ASC_{i,n,t} * Control_{i,s}, \end{aligned} \tag{2.6}$$

where λ is a vector of estimated parameters measuring the impact of the two latent variables "NEP" and "Perception" on the respondent's utility.

In our model, we define two latent constructs (LV_{NEP} and $LV_{Perception}$), measured by two sets of indicators, $I_{i,k}$. The first set of 5-point-Likert scale items measures the respondents' concerns about the environment (LV_{NEP}) (i.e., respondents' awareness about the environment), covering the 15 NEP questions in Table 2.6. The second set of 5-point-Likert scale items, with the four indicators listed in Table 2.7, is used to capture respondents' perceptions of adopting organic farming (e.g., "Is the adoption of organic farming approved by other villagers?", etc.) (see Table 2.7). The latent variables $LV_{i,k}$ used to explain the values of the indicators of attitudes and perceptions for respondent i (i.e., measurement components) are defined as follows:

$$I_{i,k} = \eta_{I_k} + h(LV_{i,k}, \zeta_{I_k}) + \psi_{I_{i,k}}, \tag{2.7}$$

where the functional form $h()$ is generally a linear specification, η is a vector of constant, ζ is a vector of estimated parameters showing the impact of the k latent variables on various indicators, and ψ is a random disturbance. Since the indicators $I_{i,k}$ are categorical variables (i.e., 5-point-Likert scale items), Equation (2.7) can be estimated using ordinal regression (i.e., Ordered Logit Model) to capture the discrete-ordered nature of the items (Daly et al., 2012). The likelihood of the observed sequence of answers to the attitudinal and perceptional questions, $L_{I_{i,k}}$, can be written as follows:

$$L_{I_{i,k}}(\zeta_{I_k}, \tau_{I_k}, LV_{i,k}) = \prod_{I_k} \left(\frac{e^{\tau_{j,I_k} - \zeta_{I_k} LV_{i,k}}}{1 + e^{\tau_{j,I_k} - \zeta_{I_k} LV_{i,k}}} - \frac{e^{\tau_{j-1,I_k} - \zeta_{I_k} LV_{i,k}}}{1 + e^{\tau_{j-1,I_k} - \zeta_{I_k} LV_{i,k}}} \right), \tag{2.8}$$

where τ is a vector of threshold parameters for the indicators in the Ordered Logit Model.

For consistency with the choice model, we apply the same set of $control_{i,s}$ presented in Equation (2.6) to $z_{i,s}$ presented in Equation (2.5) for the structural estimation of the two latent variables. We exclude the two aggregate variables, *NEP score* and *Perception score* because we have to separately estimate respondents' environmental concerns and perceptions of adopting organic farming in the measurement model components in the HCM (see Equation (2.7)). The separate identification of the parameters associated with the same characteristics (i.e., the parameters of $control_{i,s}$ and $z_{i,s}$) is ensured by the fact that for one of them, the value is driven by both the choice data and the indicator variables.

Consequently, the HCM comprises two key components: the measurement components and the choice model components. These components depend on the latent variables $LV_{i,k}$, estimated simultaneously. It should be noted that sequential estimation is possible, but it could result in a loss of efficiency. Thus, we have the combined log-likelihood as follows:

$$LL(\Omega) = \sum_{i=1}^{N} log \int_{\beta_i} \int_{LV_{i,k}} L_{C_i}(\beta_i, \gamma_i, LV_{i,k}) L_{I_{i,k}}(\zeta, \tau, LV_{i,k}) f(\beta_i) g(LV_{i,k}) d\beta_i dLV_{i,k}, \tag{2.9}$$

where $\Omega = \{\mu, \beta, \gamma_s, \gamma_{LV}, \zeta, \lambda\}$ combines all model parameters; L_{C_i} is the likelihood of an observed sequence of choices for the person i[5], $L_{I_{i,k}}$ is the likelihood of the observed sequence of answers to the k attitudinal and perceptional questions. The Log-likelihood requires the integration over the distribution of β_i and α_i and explains the presence of the density function $f(\beta_i)$ and $g(LV_{i,k})$.

Willingness to pay estimates

When estimates for parameters of the model are available, we can calculate the MWTP for each of the attributes to pass from state 3 (i.e., status quo) to the alternative n (i.e., two alternative organic options $n = \{1, 2\}$) (Hanemann, 1984; Hanley et al., 2001). The marginal WTP estimate is given by:

$$WTP = -\frac{1}{\beta_c} log\left[\frac{\sum_i exp(V_{i3})}{\sum_i exp(V_{in})}\right], \tag{2.11}$$

where β_c is the coefficient of the cost attribute.

In the traditional model, β_c is directly obtained by the regression based on the total cost variable. In reporting the WTP for attribute l (i.e., WTP_l), the log expression in Equation (2.11) simplifies to the attribute's coefficient, giving

$$WTP_l = -\frac{\beta_l}{\beta_c}. \tag{2.12}$$

In the RPL model, when the random parameter associated with the l attributes $\tilde{\beta}_l$ are normally distributed (see Equation (2.4) for the assumptions about parameter heterogeneity), we can calculate the mean WTP by

$$E(WTP_l) = -\frac{\bar{\beta}_l}{\beta_c}. \tag{2.13}$$

[5] In particular, we would have the likelihood of an observed sequence of T_i choices for the person i as follows:

$$L_{C_i}(\beta_i, \gamma_i, LV_{i,k}) = \prod_{t=1}^{T_i} \frac{e^{V_{i,n,t}}}{\sum_{j=1}^{3} e^{V_{i,j,t}}}, \tag{2.10}$$

where β_i and γ_i are groups of random and deterministic components.

2.5 Estimation results

Our results are first estimated using the CL and RPL models (see Table 2.3). The CL models, corresponding to the utility function in Equation (2.2), are first estimated without control variables (see Model (CL1) in Table 2.3). It should be noted that because of the identification issue (i.e., respondent's characteristics do not vary across choices), only interaction terms between these control variables (Female, Age, Farm size, Income, Education, Health, NEP score, Perception score, and types of agricultural products) and the ASC (i.e., Alternative Specific Constant) can be estimated. The ASC, coded as a dummy, takes a 1 if farmers prefer the "organic certification" options to the "st tus quo". Hence, the estimation with relevant interaction terms is presented in Model (CL2) (Table 2.3).

Table 2.3: Summary results of the Conditional Logit and Random Parameter Logit models.

Variable	Conditional Logit		Random Parameter Logit	
	CL 1	CL 2	RPL 1	RPL 2
Fixed parameters				
ASC	-0.389***	-4.191***	-0.794***	-4.931***
	(0.090)	(0.847)	(0.098)	(0.927)
Training and technical advice	0.685***	0.689***	-	-
	(0.044)	(0.045)		
Sales contract				
With guaranteed price	1.083***	1.089***	1.133***	1.121***
	(0.051)	(0.062)	(0.076)	(0.074)
With flexible price	0.876***	0.880***	1.063***	1.057***
	(0.061)	(0.062)	(0.075)	(0.075)
Traceability	0.513***	0.517***	0.546***	0.544***
	(0.045)	(0.045)	(0.054)	(0.054)

Neighbors	0.250***	0.256***	0.246***	0.246***
	(0.047)	(0.047)	(0.050)	(0.050)
Leadership				
Formal leader	0.393***	0.396***	-	-
	(0.077)	(0.078)		
Informal leader	0.156*	0.158*	-	-
	(0.081)	(0.082)		
Both leaders	0.280***	0.281***	-	-
	(0.065)	(0.065)		
Cost	-0.010***	-0.010***	-0.109***	-0.111***
	(0.0004)	(0.0004)	(0.007)	(0.007)
Random parameters				
Training and technical advice			0.751***	0.745***
			(0.056)	(0.054)
Leadership				
Formal leader			0.653***	0.657***
			(0.080)	(0.080)
Informal leader			0.385*	0.395*
			(0.192)	(0.189)
Both leaders			0.393***	0.393***
			(0.071)	(0.071)
Std. of random parameters				
Training and technical advice			0.826***	0.715**
			(0.195)	(0.211)
Leadership				
Formal leader			0.205	0.162
			(0.337)	(0.314)
Informal leader			0.405	0.292
			(0.441)	(0.476)

Both leaders			0.805***	0.831***
			(0.287)	(0.276)
Interaction terms				
ASC*Age		0.805***		0.969***
		(0.141)		(0.152)
ASC*Middle income		-0.139*		-0.180**
		(0.082)		(0.087)
ASC*Good health		-0.367*		-0.518**
		(0.199)		(0.211)
ASC*Very good health		-0.395*		-0.577**
		(0.214)		(0.228)
ASC*High school		0.173**		0.165*
		(0.085)		(0.090)
ASC*Perception score		0.063***		0.065***
		(0.014)		(0.016)
ASC*Rice		0.617***		0.585***
		(0.090)		(0.099)
ASC*Vegetables		0.513***		0.435***
		(0.096)		(0.103)
Observations	5,860	5,860	5,860	5,860
Log likelihood	-5241.9	-5158.1	-5377.5	-5290.7
LR χ^2(q)	(2392,q=10)	(2560,q=23)	(1359.71,q=16)	(1966.18,q=30)
p-value	< 0.001	< 0.001	< 0.001	< 0.001

Note: Standard errors in parentheses. ASC stands for Alternative Specific Constant.

Control variables, including *Female*, *Farm size*, *High income*, *College/University* and *NEP score*, are not significant at the 10% level.

LR test of CL 1 and CL 2: $\chi^2(13) = 163.34$ with $p < 0.001$. LR test of RPL 1 and RPL 2: $\chi^2(14) = 218.82$ with $p < 0.001$.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The two columns (RPL1) and (RPL2) in Table 2.3 report the results of the PL model. Model (RPL1) corresponds to the model specified by the utility function (2.3) in which the coefficients of all the attributes include random heterogeneity (2.4) and without control variables. However, we defined "Cost", "Sales contract", "Traceability" and "Neighbors" as fixed-parameter variables since the estimated standard deviation of these parameters was not significant at the one % level. Model (RPL2) is similar to Model (RPL1), but we consider the respondents' socio-demographic variables. The Likelihood ratio (LR) test of Models (RPL1) and (RPL2) is equal to $\chi^2(14) = 218.82$ with $p < 0.001$, suggesting that (RPL2) model with control variables is preferred to Model (RPL1). This result indicates that the RPL model controlling for the heterogeneity of the "Training" and "Leadership" attributes provides a significantly better representation of choices than the RPL model without controlling for socio-demographic characteristics in capturing heterogeneity among respondents.

The results of both CL and RPL models suggest that the coefficients of all of the attributes are statistically significant and have the expected sign (i.e., only the cost attribute has a negative sign, while the sign of the other attributes is positive), except for the "Informal leader" attribute. Thus, farmers appreciate providing training and technical advice, supporting sales contracts, providing logos with traceable codes (e.g., QR code), encouraging the adoption of organic certification in farmers' neighborhoods, and incentivizing formal leaders in the village to adopt organic farming. As expected, the cost attribute coefficient negatively impacts farmers' decisions, indicating that higher payment for additional production costs harms respondents utility. The results of Table 2.3 also suggest that ASC (i.e., Alternative Specific Constant) is negative and significant, meaning that farmers in our experiment positively valued staying in the "status quo" situation (i.e., farmers prefer the "status quo" to organic farming).

Hybrid Choice Model

In addition to the CL and RPL models, the HCM is presented to enrich the underlying behavioral characterizations with the explicit modeling of latent psychological variables (i.e., respondents' concerns about the environment and their perceptions of adopting organic farming) (Ben-Akiva et al., 2002; Bolduc and Alvarez-Daziano, 2010). The estimation results of Model (HCM) with two latent variables, "NEP" (LV_{NEP}) and "Perception" ($LV_{Perception}$), are reported in Table 2.4.

The first column of the results in Table 2.4 shows the estimation of the choice model component, which is estimated using the combined log-likelihood in Equation 2.9. The choice model is estimated to have the same control variables as the CL and RPL models, except for the two NEP and perception score variables that will be assessed separately in the measurement component model. The second column of Table 2.4 represents the results of the coefficients (γ) of the structural equation of the LVs defined in Equation (2.5), using the same set of control variables as in the cho ce model. In the third column of Table 2.4, the coefficients of the LVs (ζ) of the measurement component and the threshold parameters (τ) (i.e., four threshold parameters per indicator should be estimated since we have 5-point-scale dependent variable calculated using the Ordered Logit Model.

A comparison of Tables 2.3 and 2.4 leads to the following conclusions. The result of the HCM confirms that the ASC has a negative and statistically significant impact on respondents' choices. It suggests that farmers generally seem to be less willing to participate in organic certification schemes (i.e., they prefer the "status quo" to the organic certification options). Based on our follow-up survey, we observe that Vietnamese farmers prefer the "status quo" option is because there is a lack of subsidies and information related to organic agriculture. In particular, we observe about 7% of farmers always chose the "status quo" option. A majority of these farmers claimed that they do not prefer organic certification alternatives because they believe that none of their neighbors is involved in organic farming (37.21%), lack sufficient information related to organic farming (34.88%), lack subsidies from the government (27.91%) and too difficult to market organic products (25.58%).

Table 2.4: Summary results of the Hybrid Choice Model with "NEP" and "Perception" as the latent variables.

	HCM				
Variable	Coef.	Variable	Coef.	Variable	Coef.
Choice model component		**Socio-demographic variables on LV "*NEP*"**		**LV "Concern" on its indicators**	
ASC	-6.996***	$\gamma_{NEP,Female}$	-0.091	$\zeta_{NEP,1}$	0.882**
	(2.387)		(0.153)		(0.399)
Training and technical advice	0.753***	$\gamma_{NEP,Age}$	0.530*	$\zeta_{NEP,2}$	-1.090**
	(0.057)		(0.288)		(0.455)
Sales contract with fixed price	1.193***	$\gamma_{NEP,FarmSize}$	0.080	$\zeta_{NEP,3}$	0.830***
	(0.069)		(0.079)		(0.250)
Sales contract with flexible price	0.954***	$\gamma_{NEP,MiddleIncome}$	-0.059	$\zeta_{NEP,4}$	-1.545***
	(0.079)		(0.177)		(0.476)
Traceability	0.590***	$\gamma_{NEP,HighIncome}$	-0.106	$\zeta_{NEP,5}$	1.211***
	(0.062)		(0.371)		(0.435)
Neighbors	0.345***	$\gamma_{NEP,GoodHealth}$	-0.253	$\zeta_{NEP,6}$	-1.837***
	(0.057)		(0.652)		(0.435)
Formal leader	0.410***	$\gamma_{NEP,VeryGoodHealth}$	-0.108	$\zeta_{NEP,7}$	1.852***
	(0.110)		(0.807)		(0.447)
Informal leader	0.150	$\gamma_{NEP,HighSchool}$	0.078	$\zeta_{NEP,8}$	-0.206
	(0.121)		(0.129)		(0.190)
Both leaders	0.265***	$\gamma_{NEP,College}$	0.280	$\zeta_{NEP,9}$	1.453
	(0.097)		(0.511)		(0.223)
Cost	-0.011***	$\gamma_{NEP,Rice}$	-0.129	$\zeta_{NEP,10}$	-0.442**
	(0.0007)		(0.311)		(0.196)
λ_{NEP}	0.056	$\gamma_{NEP,Vegetable}$	-0.412	$\zeta_{NEP,11}$	1.493***
	(0.453)		(0.417)		(0.287)
$\lambda_{Perception}$	3.033***			$\zeta_{NEP,12}$	-1.067***
	(0.363)	**Socio-demographic variables on LV "*Perception*"**			(0.183)
Interaction terms					
ASC*Female	-1.465	$\gamma_{Perception,Female}$	0.505	$\zeta_{NEP,13}$	1.405***
	(1.202)		(0.366)		(0.497)
ASC*Age	-7.289***	$\gamma_{Perception,Age}$	2.954***	$\zeta_{NEP,14}$	-1.417***
	(0.839)		(0.391)		(0.270)
ASC*Farm size	-0.885	$\gamma_{Perception,FarmSize}$	0.338**	$\zeta_{NEP,15}$	1.763***
	(0.950)		(0.133)		(0.296)
ASC*Middle income	-2.153*	$\gamma_{Perception,MiddleIncome}$	0.609		
	(1.310)		(0.430)	**LV "Perception" on its indicators**	
ASC*High income	-2.832***	$\gamma_{Perception,HighIncome}$	0.695	$\zeta_{Perception,1}$	0.222***
	(0.834)		(0.433)		(0.045)
ASC*High school	-5.071***	$\gamma_{Perception,GoodHealth}$	0.140	$\zeta_{Perception,2}$	0.356***
	(1.325)		(0.920)		(0.126)
ASC*College	-10.344***	$\gamma_{Perception,VeryGoodHealth}$	0.147	$\zeta_{Perception,3}$	0.200***
	(0.784)		(0.348)		(0.052)
ASC*Good health	-0.974	$\gamma_{Perception,HighSchool}$	1.845 ***	$\zeta_{Perception,4}$	0.292***
	(1.844)		(0.556)		(0.076)
ASC*Very good health	-0.771	$\gamma_{Perception,College}$	3.398***		
	(1.182)		(0.450)		
ASC*Rice	1.048	$\gamma_{Perception,Rice}$	-0.062		
	(1.317)		(0.559)		
ASC*Vegetable	1.678	$\gamma_{Perception,Vegetable}$	-0.325		
	(1.569)		(0.366)		
Observations	5,860	LL of the combined model	-16780.95	AIC	33841.90
Estimation time	87h:52m:51s	LL of the choice model	4369.11	BIC	34776.53
Number of parameters	140				

Note: Estimation performed on a 4-cores and 8Gb RAM computer.
Robust standard errors in parentheses. ASC stands for Alternative Specific Constant.
Threshold parameters τ of the measurement component of LV "NEP" and LV "Perception" are estimated, but they are reported.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The estimates of the coefficients of the Model (HCM) attributes are close to the RPL model, with all attributes being positive and statistically significant, except for the "Informal leader" and "Cost" attributes. Thus, these results confirm that the "Informal leader", defined as the presence of informal leaders (e.g., religious leaders or the most successful farmers in the village, etc.) having adopted organic farming, has no significant effect on promoting farmers toward organic ag iculture. One possible explanation should be that, unlike people in the cities, farmers in Vietnamese rural areas often have close ties/connections to their formal leaders (e.g., frequent interactions with their village leaders). Moreover, rural farmers usually rely on their formal leaders (e.g., village leaders or the president of farmers' associations) to obtain information, knowledge, and practical lessons about organic farming. As a result, they prefer to have either formal leaders or both leaders (formal and informal) in their villages to support them in accessing organic certification schemes (Pielstick, 2000; Sleeth-Keppler et al., 2017).

In addition to the "Leadership" attribute, the "Neighbors" attribute, defined as the coordination with neighborhood farmers in the village involved in organic farming, has a positive and statistically significant impact on farmers' decisions to engage in an organic certification scheme. This result indicates that a network of farmers (e.g., neighbors or friends) could play an essential role in promoting organic farming because farmers living in rural areas frequently interact with their neighbors/friends since they always live nearby and thus know each other well (i.e., they have strong connections with their neighbors). This result is in line with the existing literature since individual-to-individual links are essential and valuable sources of information, knowledge, and reflection for individuals that could help significantly motivate people to behave positively toward pro-environmental behaviors (Axsen et al., 2013; Jackson, 2010; Lazaric et al., 2019; Olli et al., 2001).

Regarding the effect of the latent variables on farmers' choices, we observe that the coefficient $\lambda_{Perception}$ is positive and statistically significant in Table 2.4, while the coefficient λ_{NEP} is not statistically significant. Moreover, we observe that the coefficients $\zeta_{Perception}$ (including $\zeta_{Perception,1}$, $\zeta_{Perception,2}$, $\zeta_{Perception,3}$ and $\zeta_{Perception,4}$, which represent the impacts of the LV "Perception" on the four perceptional indicators listed in Table

2.7) are positive and significant, suggesting that a higher value of the latent variable corresponds to the more substantial perception of organic farming. These results indicated that individuals who have a stronger perception of adopting organic agriculture (e.g., they believe that it is helpful for farmers to adopt organic farming to protect the environment and the health of the population) would be more likely to participate in organic certification schemes than others w o do not. This result confirms our prior expectations that farmers' motivation to adopt sustainable agricultural practices is associated with their pro-environmental beliefs and perceptions regarding the importance of environmental conservation K. B. My et al., 2022; Nguyen-Van et al., 2021; Tiet, Nguyen-Anh, et al., 2022.

The results of the structural model components in Column (2) of Table 2.4 suggest that $\gamma_{Perception,Age}$ is positive and significant, indicating that older farmers have a more robust perception of adopting organic farming and thus have a higher possibility of engaging in organic certification schemes. Indeed, older farmers are often aware of health risks and care more about their future generations (e.g., children and grandchildren), and therefore, they are more likely to engage in organic farming and environmentally friendly practices than younger generations (Peterson et al., 2012). Moreover, larger-scale farmers (i.e., those with larger farms) seem to have a more vital perception of organic farming than smaller-scale ones (i.e., $\gamma_{Perception,FarmSize}$ is positive and significant). One reason could be that small-scale farmers often face financial difficulties and have less capability to adopt new and costly farming practices (e.g., organic farming) than large-scale farmers. Therefore, smaller-scale farmers are less likely to be involved in organic certification schemes.

Concerning farmers' levels of education, we observe that a higher level of education (i.e., farmers who graduated from high school, college, or university) is associated with a more robust perception of organic farming conversion. This result reveals that farmers with better education are more concerned about organic agriculture and, thus, more willing to behave positively toward organic farming than others. Evidence showed that educated farmers are eager to participate in agricultural extension programs and, therefore, have a higher incentive to adopt organic farming practices because farmers' education is linked to their capacity to acquire technical information (Hoang-Khac et al., 2021). Education level and information accumulation are associated with farmers' innovative ability and thus could improve the probability of adopting new technology (Genius et al., 2006).

Estimation of willingness to pay

Table 2.5 reports the calculation of the mean WTPs for all the attribute levels using two different Models (RPL2) and (HCM). We also look at the differences in WTPs for different agricultural products (i.e., rice, vegetables, and other products). We observe that the WTP estimation results of these two models are very close. It should be noted that the WTPs are calculated when both parameters (i.e., β_n and β_c; see Equation (2.11)) used in the calculation are statistically significant; otherwise, no meaningful WTP measure can be es established. For this reason, there is no WTP estimate for informal leadership or formal leadership attributes in some cases since their coefficient estimates are not statistically significant at the 10% level.

According to the result in the Model (HCM), we observe that farmers are willing to pay an increase in production cost up to 9.805 thousand VND/kg (i.e., about 68% more than the average current production cost) to engage in organic certification schemes that provide practical lessons and have technicians or specialists advise them to convert to organic farming. Farmers seem to be willing to pay a higher production cost to be involved in an organic certification scheme that offers a sales contract with buyers or retailers (e.g., industries, supermarkets, direct consumers, etc.) on the order of 12.118 and 10.859 thousand VND/kg (i.e., about 107% and 85% more than the average current production cost) for sales contracts with guaranteed prices and flexible prices, respectively. Our result suggests that farmers prefer the contract with fixed/guaranteed prices (i.e., product prices are fixed over five years) to the one with flexible prices (i.e., product prices float with market prices). Farmers are willing to pay an increase in production cost up to 8.945 thousand VND/kg (i.e., about 53% more than the average current production cost) to obtain an organic logo with a traceable code on their products. The "Neighbors" and "Leadership" attributes are also crucial since farmers are willing to pay a higher production cost to have the opportunity to coordinate with neighbors and leaders in their village in doing organic farming.

The estimated WTAs or WTPs are of significant importance to policymakers. The relative importance of the attributes can be derived from their WTA and WTP values, whereby those with higher WTAs or WTPs are assigned more resources than the others. In this study, farmers' WTPs changes in production cost to engage in organic certification schemes, including sales contracts with guaranteed and flexible prices, are consistently higher than other attributes. This result shows that organic farmers highly value sales contracts with buyers or retailers to ensure their products can be sold at flexible or fixed prices. This result is consistent with intuition since guaranteed product prices and outcomes are essential because most farmers in our study are smallholder farmers. The existing literature has argued that smallholder farmers in Vietnam strongly depend on traders to sell their products, but traders are the ones who set the price, and farmers have to pay the price offered to them (Minot, 2006). These results are intuitive because sales contracts are directly linked to organic agriculture's profit or revenue, a significant barrier to adopting organic farming (Läpple and Kelley, 2013; Schneeberger et al., 2002). On the other hand, organic neighbors do not have a direct link to income from farming. However, they could help each other by sharing recommendations, advice, knowledge, and important tips during the implementation of organic agriculture, which is also crucial for maintaining long-run sustainable behavior (Genius et al., 2006; Hall and Rhoades, 2010).

Table 2.5: Estimated willingness to pay (WTP) for the attribute levels.

	HCM	**RPL 2**			
Attributes	All products	All products	Rice	Vegetables	Others
Training and technical advice	9.805	8.993	8.898	10.806	8.112
	[9.091, 10.519]	[8.374, 9.612]	[8.064, 9.733]	[9.538, 12.075]	[7.418, 8.806]
Sales contract					
With guaranteed prices	12.118	10.785	9.889	14.289	9.888
	[11.220, 13.015]	[10.037, 11.534]	[8.989, 10.789]	[12.721, 15.858]	[9.416, 10.361]
With flexible prices	10.859	9.560	9.067	11.898	7.738
	[9.821, 11.897]	[8.698, 10.422]	[7.981, 10.153]	[10.172, 13.623]	[7.220, 8.256]
Traceability	8.945	8.011	7.869	9.801	7.771
	[8.270, 9.620]	[7.391, 8.631]	[7.008, 8.731]	[8.629, 10.973]	[7.246, 8.295]
Neighbors	7.656	7.495	7.289	7.565	7.510
	[7.072, 8.240]	[7.017, 7.972]	[6.604, 7.975]	[6.486, 8.644]	[7.049, 7.971]
Leadership					
Formal leader	7.999	6.967	7.993	-	-
	[6.757, 9.241]	[6.078, 7.856]	[6.676, 9.310]		
Both leaders	7.238	6.935	7.494	-	6.886
	[6.194, 8.282]	[6.228, 7.643]	[6.484, 8.504]		[6.273, 7.499]

Note: WTAs are in thousands of VND/kg.
Confidence interval (CI) at the 5% significance level. Standard deviation is calculated by the delta method (for computation details, see the paper of Hole, 2007).
Model (HCM) is the Hybrid Choice Model with two LV variables, “Perception” and “Concern”.
The WTA estimates are calculated from the results of Models (HCM) and (RPL 2), which are the models with socio-demographic and psychological control variables. The “All products” is the model with all three types of agricultural products.
There is no WTA estimate for the “Informal leader” attribute because the coefficient estimates are not statistically significant at the 10% level.

Looking at the results for different agricultural products (including rice, vegetables, and others), we observe that farmers generally have a positive WTP for organic farming. Moreover, the “formal leader” attribute only significantly impacts rice producer WTPs. In other words, only rice farmers are willing to pay a higher production cost to have local leaders (formal or informal) involved in organic agriculture. This result could be because organic rice often has limited demand and inadequate marketing (i.e., more significant challenges to market organic rice products) than organic vegetables or other types of products (Chouichom, Yamao, et al., 2010; Mishra, Kumar, Joshi, D'Souza, and Tripathi, 2018). Consequently, smallholder rice producers are willing to pay increased production costs to have leaders involved in organic farming in their villages. Therefore, the leaders could help share their knowledge and practical lessons with local farmers and provide the information necessary to market their crops.

2.6 Discussions and conclusions

This paper aims to investigate farmers' preferences for adopting organic agriculture. We use a quantitative approach based on a discrete choice experiment with 586 farmers in Northern Vietnam to measure how various factors could influence farmers' decisions to adopt organic agriculture. We value farmers' WTPs for both market and non-market components of their choices, such as practical training lessons and local technical advice, sales contracts with guaranteed or flexible prices with retailers (e.g., direct consumers, supermarkets, industries, etc.), organic logos with traceable codes, coordination with neighbors and presence of leaders in their village involved in organic farming.

Our results suggest that all the above attributes could significantly impact farmers' decisions to engage in organic certification schemes. Firstly, we found that sales contracts with flexible or guaranteed prices are significant incentives that explain farmers' willingness to pay a higher production cost to participate in organic certification schemes. Most farmers in our study are smallholders who always experience difficulties marketing their crops and accessing new markets. Consequently, the buyers' commitment to the outcome of agricultural products is seen as an opportunity to support organic agriculture. This result aligns with the literature on "contract farming," in which the purchaser provides farmers with credit, technical advice, market services, etc. In return, farmers produce a certain quantity and quality of products and sell them to the purchaser (Bellemare and Novak, 2017; Bolwig et al., 2009; Dubbert, 2019). Therefore, such an arrangement could positively contribute to farmers' revenues, in particular, as well as to growth and the reduction of poverty, in general (Bellemare and Lim, 2018; Krah et al., 2018; Mishra, Kumar, Joshi, and D'Souza, 2018; Ruml and Qaim, 2021; Weiss and Khan, 2006).

Secondly, the "traceability" attribute is also essential in encouraging the adoption of organic certification. Farmers who want a sales contract often require a logo with a traceable code because it indicates that their organic products have undergone strict quality controls and production monitoring systems. Additionally, consumers are always more likely to pay higher prices for higher-quality foods. Thus, a logo with a traceable code could also help them distinguish high-quality organic foods from low-quality ones. As a result, traceability is the best tool for food quality control and encourages consumer confidence in organic products (Messer et al., 2017; Shimokawa et al., 2021; Spence et al., 2018; Wu et al., 2011). Therefore, an organic logo accompanied by a transparent traceability system is essential to promote competitive pricing and expanded access to high-quality and safe agricultural products, which could boost domestic demand.

Thirdly, in addition to the market factors, training, and technical advice are dominant non-market factors that motivate farmers to move toward organic agriculture. This result is straightforward because several existing studies suggest that technical knowledge of organic farming practices is a critical barrier to the transition to organic farming (Brock and Barham, 2013; Dimitri and Baron, 2019; Hoque et al., 2021; Van Campenhout et al., 2020). For instance, providing farmers with agricultural advisory services (i.e., agricultural extension agents visit farmers and provide them with agrarian information) could promote sustainable agriculture (Norton and Alwang, 2020; Park and Lohr, 2007). Therefore, providing training and technical assistance to farmers via village leaders or the president of the farmers' association as public extension agents could also be an effective way to motivate the adoption of organic farming since we observe that farmers in the survey areas care far more about the participation of their formal leaders in doing organic farming.

Fourthly, our results shed light on the role of coordination with neighborhood farmers in promoting farmers' adoption of sustainable agricultural practices in the survey areas. This result is in line with the existing literature that programs targeting specific individual farmers (e.g., "seed" farmers, "progressive" farmers, or early adopters) could effectively help to modify farmers' behavior (Läpple and Kelley, 2015; Maertens, 2017;

Norton and Alwang, 2020; Nyblom et al., 2003; Wollni and Andersson, 2014). In their study, the authors argued that individual farmers are less likely to apply the organic practices that help restore soil function because they fear that their neighboring farmers may free-ride on their investments in the soil and fertility improvements unless all farmers in the neighborhood commit to this organic practice (Di Falco et al., 2020; Wollni and Andersson, 2014). Therefore, encouraging neighborhood cooperatives rather than prioritizing programs for individual farmers could be more effective in promoting farmers to adopt organic farming practices.

Finally, the results of the HCM model suggest that farmers' perceptions of adopting organic farming play a significant role in encouraging farmers to engage in organic certification schemes. We also observe that a higher level of perception of organic farming requires farmers to know the importance of organic agriculture in protecting the environment and population health and their awareness of the benefits of organic agricultural production. Thus, education, training, and information about organic farming standards, technologies, and practices are essential for farmers to enhance their knowledge and capacity to use sustainable farming practices, organic agricultural production, and new market situations (Nguyen-Van et al., 2021; Tiet, Nguyen-Anh, et al., 2022). Networking and social interactions in the local area should be encouraged to promote knowledge sharing among neighborhood farmers and strengthen the connections with different farmers' groups, such as local government agencies and private sectors (K. B. My et al., 2022).

Limitations and future research directions

There are, of course, limitations of our analysis that must be considered when interpreting the findings of the results. In particular, while farmers who participated in our research were not adopting organic farming practices, we did not control for differences in their existing farming techniques. Thus, future studies should also collect and examine this type of information. Furthermore, we only investigate farmers' decisions to adopt organic certification schemes in Northern Vietnam due to data constraints. Larger and more diverse sample sizes of farmers could also enhance DCE findings by offering more profound insights and enhancing extrapolation on power. Moreover, future studies should take subjects' stated attribute non-attendance in their DCE studies and carefully formulate follow-up questions regarding subjects' reasons for ignoring attributes for dealing with heterogeneous attribute processing strategies (Alemu et al., 2013; Scarpa et al., 2013).

Our study found that farmers' WTPs vary across agricultural products (e.g., rice, vegetables, fruits, co n, etc.). For instance, rice producers are the only ones willing to pay a higher production cost to have formal leaders or both formal and informal leaders in their villages involved in organic farming because certain types of organic agricultural products (like rice) are more difficult to market than organic vegetables or other types of products. Consequently, further research is still needed to establish the actual costs and benefits of adopting organic farming by considering the different types of agricultural products. The complementary cost-benefit analysis can additionally provide policymakers with other benefits that may result from the long-term reduction of pesticide use and the use of other harmful plant protection products. The long-run discount rate should also be considered since the investment in organic agriculture has welfare effects for future generations.

2.7 Supporting information

2.7.1 Tables

Table 2.6: The 15 NEP scale items and their response distributions (in percentage).

NEP scale items	Strongly disagree	Partly disagree	Unsure	Partly agree	Strongly agree	Corr
1: "We are approaching the limit of the number of people the earth can support".	6.14	24.74	17.06	40.96	11.09	0.471
2: "Humans have the right to modify the natural environment to suit their needs".[a]	7.68	15.87	6.83	55.46	14.16	0.477
3: "When humans interfere with nature it often produces disastrous consequences".	9.73	31.40	10.24	38.74	9.90	0.469
4: "Human ingenuity will ensure that we do not make the earth unlivable".[a]	5.63	9.22	8.70	63.82	12.63	0.557
5: "Humans are severely abusing the environment".	7.68	21.33	4.10	48.12	18.77	0.542
6: "The Earth has plenty of natural resources if we just learn how to develop them".[a]	4.44	2.22	4.44	71.50	17.41	0.617
7: "Plants and animals have as much right as humans to exist".	3.75	7.00	4.78	65.87	18.60	0.611
8: "The balance of nature is strong enough to cope with the impacts of modern industrial nations".[a]	11.09	39.25	16.55	28.16	4.95	0.316
9: "Despite our special abilities, humans are still subject to the laws of nature".	3.75	3.92	1.88	70.31	20.14	0.556
10: "The so-called "ecological crisis" facing humankind has been greatly exaggerated".[a]	9.56	43.34	18.09	25.94	3.07	0.381
11: "The Earth is like a spaceship with very limited room and resources".	3.41	6.14	8.02	67.58	14.85	0.571
12: "Humans were meant to rule over the rest of nature".[a]	5.63	23.04	16.04	46.76	8.53	0.505
13: "The balance of nature is very delicate and easily upset".	3.24	12.46	12.80	63.14	8.36	0.524
14: "Humans will eventually learn enough about how nature works to be able to control it".[a]	3.58	18.60	9.22	59.56	9.04	0.535
15: "If things continue on their present course, we will soon experience a major ecological catastrophe".	3.58	6.31	7.00	64.16	18.94	0.570
Total NEP score		Mean = 47.60 and SD = 4.62.				
Cronbach's alpha			0.7902			

Notes: [a] Reverse coded.

The column Corr represents the item-test correlation, which tells us how much each items correlates with the total NEP score. Cronbach's alpha is equal to 79.02 % in the reliability test, which suggests that 79.02% of the variance in the score is reliable.

Table 2.7: Descriptive statistics of perceptional variables (in percentage).

Item	Description	Strongly disagree	Disagree	Unsure	Agree	Strongly agree
Perceptions of organic farming						
*Perception*1	Food safety problem was seriously caused by abuse of pesticides and fertilizers in farming.	3.58	6.83	1.37	57.00	31.23
*Perception*2	It is useful for farmers to adopt organic farming to protect the environment and the health of the population.	2.39	0.68	1.37	66.21	29.35
*Perception*3	Adopting organic farming practices is common in the village.	7.85	23.04	14.85	46.76	7.51
*Perception*4	Most of the other villagers approve of adopting organic farming practices during production.	2.39	9.56	20.99	58.02	9.04
Total perception score		Mean = 15.1 and SD = 2.35. Cronbach's alpha = 0.51				

Table 2.8: Correlation matrix of nine indicators of the "NEP" and "Perception" latent variables (with Pearson's correlation test).

	NEP 1	NEP 2	NEP 3	NEP 4	NEP 5	Perception 1	Perception 2	Perception 3	Perception 4
NEP 1	1.00								
NEP 2	-0.20	1.00							
	(0.00)								
NEP 3	0.28	-0.04	1.00						
	(0.00)	(0.00)							
NEP 4	-0.13	0.31	-0.19	1.00					
	(0.00)	(0.00)	(0.00)						
NEP 5	0.25	-0.09	0.42	-0.28	1.00				
	(0.00)	(0.00)	(0.00)	(0.00)					
Perception 1	0.17	-0.06	0.13	-0.11	0.21	1.00			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
Perception 2	0.15	-0.11	0.11	-0.21	0.16	0.40	1.00		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
Perception 3	0.06	-0.06	-0.02	-0.07	0.00	-0.03	0.16	1.00	
	(0.00)	(0.00)	(0.02)	(0.00)	(0.60)	(0.00)	(0.00)		
Perception 4	0.07	-0.05	0.00	-0.16	0.04	0.11	0.33	0.40	1.00
	(0.00)	(0.00)	(0.54)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Notes: The p-values of the Pearson correlation test statistics are in parentheses.
The Pearson correlation test statistics suggest that the correlation between the indicators of the two latent variables exist. However, the correlation coefficients of these indicators are not too large (i.e., a majority of the correlation coefficients are below 0.20).

Table 2.9: Summary results of the Random Parameter Logit models with Cost parameter following truncated normal distribution.

Variable	Random Parameter Logit	
	RPL 2	RPL 3
Fixed parameters		
ASC	-4.931***	-6.466***
	(0.927)	(1.131)
Sales contract		
With guaranteed price	1.121***	1.521***
	(0.074)	(0.119)
With flexible price	1.057***	1.460***
	(0.075)	(0.095)
Traceability	0.544***	0.741***
	(0.054)	(0.075)
Neighbors	0.246***	0.511***
	(0.050)	(0.102)
Cost	-0.111***	-
	(0.007)	
Random parameters		
Training and technical advice	0.745***	1.018***
	(0.054)	(0.081)
Leadership		
Formal leader	0.657***	0.956***
	(0.080)	(0.104)
Informal leader	0.395*	0.539*
	(0.189)	(0.264)
Both leaders	0.393***	0.442***
	(0.071)	(0.112)
Cost	-	-0.403**
		(0.112)
Std. of random parameters		
Training and technical advice	0.715**	1.589**
	(0.211)	(0.201)
Leadership		
Formal leader	0.162	0.745
	(0.314)	(0.474)
Informal leader	0.292	1.173**
	(0.476)	(0.426)
Both leaders	0.831***	2.847**
	(0.276)	(0.425)
Cost	-	0.115***
		(7.627)
Interaction terms		
ASC*Age	0.969***	1.024***
	(0.152)	(0.189)
ASC*Middle income	-0.180**	-0.152*
	(0.087)	(0.103)
ASC*Good health	-0.518**	-0.260
	(0.211)	(0.237)
ASC*Very good health	-0.577**	-0.319**
	(0.228)	(0.158)
ASC*High school	0.165*	0.216*
	(0.090)	(0.108)
ASC*Perception score	0.065***	0.084***
	(0.016)	(0.019)
ASC*Rice	0.585***	0.797***
	(0.099)	(0.122)
ASC*Vegetables	0.435***	0.627***
	(0.103)	(0.124)
Observations	5,860	5,860
Log likelihood	-5290.7	-5180.2
LR χ^2(q)	(1966.18,q=30)	(1966.18,q=30)
p-value	< 0.001	< 0.001

2.7.2 Figures

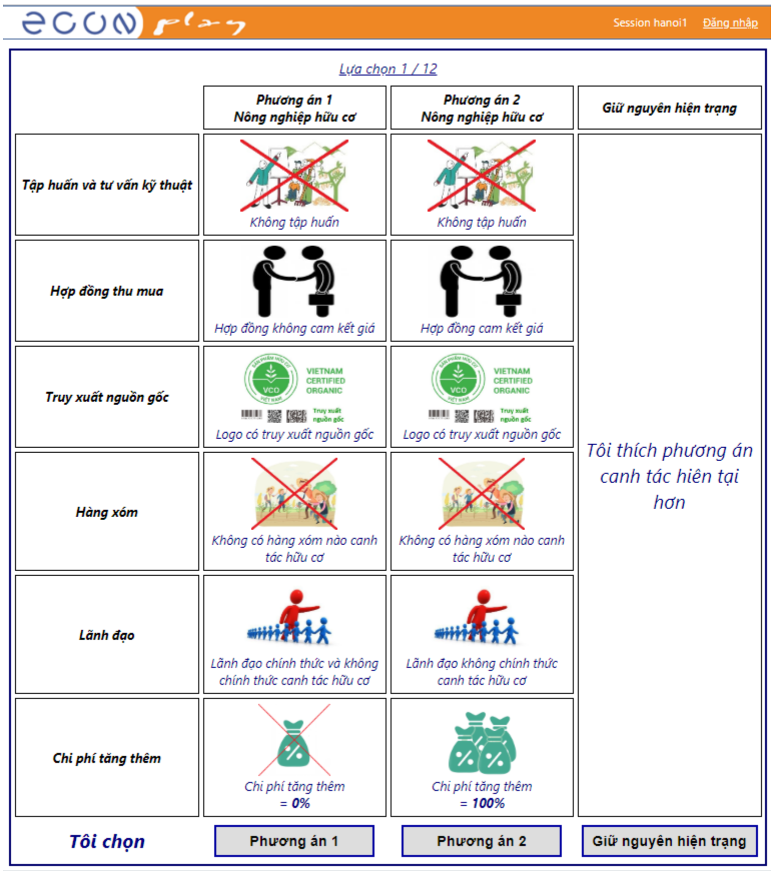

Figure 2.2: Example of choice card (in Vietnamese).

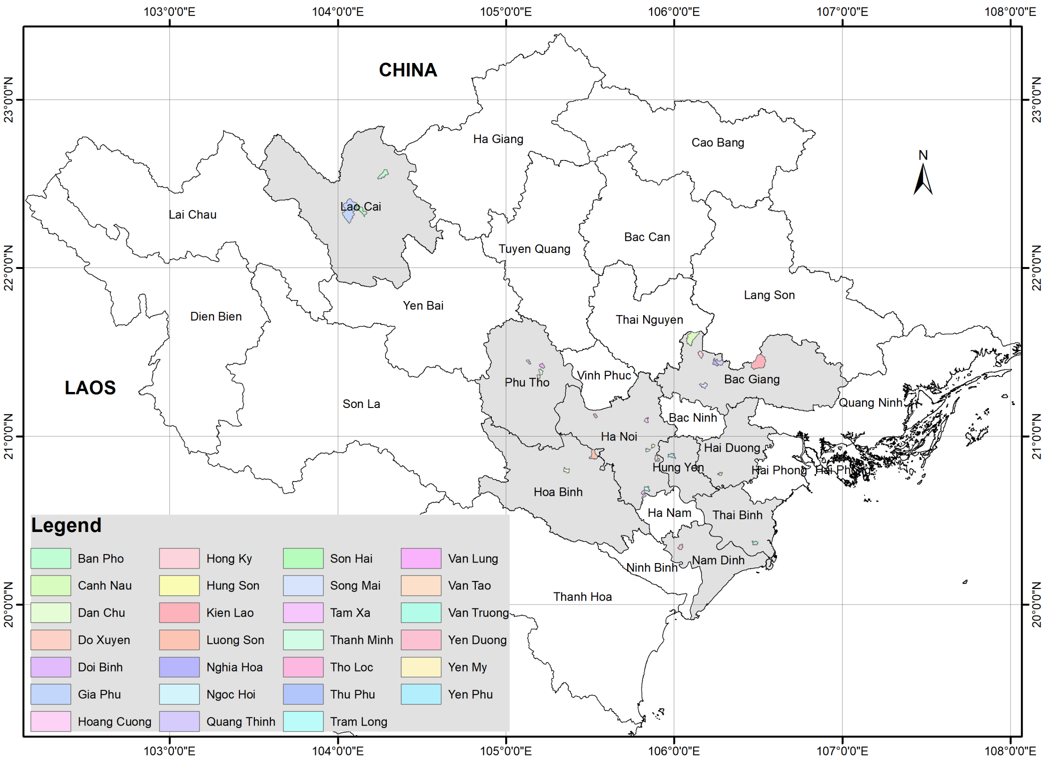

Figure 2.3: Experimental areas.

Chapter 3

Cooperation in organic agriculture adoption: A theoretical model

Summary

We analyze farmers' production risk when deciding between conventional agriculture and adopting organic agriculture. Our model designates the informed farmer as a leader within the group. The leader receives information about organic technology and decides on land allocation to organic agriculture before other farmers. We develop three primary scenarios: (1) Decision-making under symmetric information, (2) Decision-making under asymmetric information, and (3) Decision-making under asymmetric information with a bargaining model. Our model predicts that farmers will follow the leader's decision if they know it is optimal. We demonstrate that risk-averse farmers allocate less land to organic agriculture than other risk attitudes. The Nash-bargaining solutions predict an equal share of potential gains from information diffusion. Based on the model, we recommend implementing a mechanism to facilitate information exchange among farmers to promote the adoption of organic agriculture.

Keywords: Organic agriculture; Decision-Making under Risk; Nash-bargaining model.
JEL code: C61; C71; D82; Q50

3.1 Introduction

Adopting organic agriculture is sustainable production and helps preserve the degrading environment caused by conventional agriculture [1] (Meemken and Qaim, 2018). Organic agriculture requires harmony in the local area, including local forest, and then the pressures of deforestation for land use decrease per unit of land (Meemken and Qaim, 2018). From many studies, the biodiversity in organic areas is more prosperous than conventional ones by reserving different species and plants (Schneider et al., 2014).

In the view of farmers, organic agriculture creates a higher premium per unit of product sold on the market (Jouzi et al., 2017) because the consumers agree to pay a better price for those products. Besides, the organic agricultural method improves the soil quality through carbon reservation and then increases the pet-resistant capacity of the crop (Seufert et al., 2017). Thus, farmers have positive reasons for adopting organic agriculture for their benefit and the environment.

However, farmers face difficulties in adopting, which lie mainly in productivity uncertainty and related costs (in the conversion and production phase) (Mzoughi, 2011). Concerning organic farming, the crop's yields are relatively lower than those of conventional agriculture (Eyhorn et al., 2019; Jouzi et al., 2017). Their adoption has higher risks because of the higher yield variation (Knapp and van der Heijden, 2018). Thus, the combination of lower yield and productivity uncertainty reduces the possibility of getting higher benefits from adopting organic agriculture. Therefore, farmers hesitate to change from conventional agriculture to organic one (Kallas et al., 2010).

Especially farmers in developing countries have more difficulties in adopting organic agriculture because their land sizes are usually smaller than those in developed countries; land size plays a vital role in reducing the yield gap between organic agriculture and conventional agriculture, and this creates a more significant disadvantage for smallholder farmers (Ramankutty et al., 2019). Although organic products bring those farmers a

[1] The term "conventional agriculture" means the standard method used in planting, nurturing, and harvesting agricultural products. The methods include extensive use of synthetic fertilizers and pesticides (Meemken and Qaim, 2018; Mzoughi, 2011)

higher premium than conventional ones, they have to pay a higher, remarkably certified cost; they are more vulnerable to environmental change, so their productivity varies significantly (Jouzi et al., 2017). Thus, the question raised is how farmers overcome the risks of adoption to practice organic methods.

In this paper, we focus on coping with adopting organic agriculture under the risks mentioned in the previous paragraphs. Considering that farmers face the situation that they are free to adapt their land to new agricultural types and give up partly or wholly their conventional type, they do not have enough information to guarantee the final benefits of their decisions. Many studies supported the notion of *first-mover* in the situation of making decisions under risks or incomplete information (Potters et al., 2005, 2007; Vesterlund, 2003). Those studies build the models on which people contribute money to different funds. Givers know that there are "good" and "bad" funds, but they do not know which one is "good" or "bad". The information is incomplete, and the decision is risky. The givers can optimize their choice and get the best benefit by observing the *first-mover's* action (Vesterlund, 2003).

The first-mover complies with the definition of leadership-by-example and prestige leadership in many studies (Henrich et al., 2015; Hermalin, 1998). Leaders have better information than the others in the group and can deliver or take action as an example to urge others to follow. The leadership proves its efficiency in solving the problem of the decisions in a group and under risk to achieve better individual and collective benefits (Kosfeld and Rustagi, 2015; Pietraszewski, 2020). In our model, we introduce leadership as a solution for searching for information and then delivering it to farmers. Under the leadership guide, they overcome the information problem to decide on adoption.

We aim to answer whether leadership influences farmers' decision to adopt organic agriculture. If all receive the same information, we show that followers decide independently with the leader to choose their allocation level. While in the asymmetric information case, the leader utilizes the state of technology given to invest in organic land, their decision influences the followers if the leader's investment is the same in theoretical prediction: the follower mimics the same investment levels to obtain the highest expected utility. This behavior leads to a zero gain from the bargaining model, so both farmers do not exchange information. We use the subsidy for organic production, so leaders always converse about the organic technique. In this situation, the follower cannot mimic the leader's decision to optimize their income. Therefore, we prove that gains from information positively motivate farmers to join a bargaining process to share the information. Our result shows that the farmers agree to share the benefits with the leader to obtain the information. The shares depend on each farmer's bargaining powers: the farmer with higher bargaining power gets more advantage in the negotiation than the other.

3.2 Basic model

We consider the following setting: Two farmers live in a community and possess the land for agriculture.

One farmer is the leader, denoted l. As a leader, they have to conserve organic agriculture and make decisions before the other farmers in their group.

One farmer is a follower, denoted f. As a follower, they can decide whether to adopt organic agriculture or stay in the current practice. However, their decision is made after observing the leader's choice.

Farmer's income comes from agriculture using conventional technology. Suppose that production function for farmer i using conventional technology, $i = (l, f)$, in their z_i land units is $q_c(z_i) = bz_i$, where $b > 0$ is the marginal productivity; the corresponding cost function is $C_c(z_i) = cz_i^2$, where $c > 0$.

Now, farmers can choose to do agriculture with organic technology, or organic agriculture for short. Suppose that production function for farmer i using organic technology in their x_i land units is $q_o(x_i) = \beta x_i$, $\beta > 0$ and the corresponding cost function is $C_o(x_i) = \alpha x_i^2$, where $\alpha > 0$. Like in conventional technology, farmers use the same organic technology, and then β and α are the same for farmers.

For simplicity, each farmer has one land unit, and they use all of the land in agricultural production; the price of conventional output is 1; the price of organic output is $p > 1$. Suppose that farmer i allocates $x_i \in [0, 1]$, $i = (l, f)$ land on organic technology, then $1 - x_i$ is land using in conventional technology. A subsidy comes from the government's goal of developing sustainable agriculture $s_i > 0$, which will be transferred to farmers if they choose organic practice. The amount of support depends linearly on the farmer's investment in organic agriculture: farmers who cultivate x_i land for organic agriculture receive $s_i x_i$ financial support from the government. The subsidy rate may be different for the leader and the follower.

Given our above setting, farmer's income from organic and conventional technology is

$$\begin{aligned} \pi(x_i) &= \underbrace{-(\alpha + c)x_i^2 + (p\beta - b + 2c)x_i + b - c}_{\text{income from agriculture}} + \underbrace{s_i x_i}_{\text{subsidy}} \\ &= -(\alpha + c)x_i^2 + (p\beta - b + 2c + s_i)x_i + b - c \end{aligned} \tag{3.1}$$

3.2.1 Organic technology

We consider that there are two states of organic technology. Each agricultural season has only one state, the true state, for two farmers. If the first state is the true state, denoted (β_H, α_H), farmers always receive a higher income than when the second state, denoted (β_L, α_L), is the true state. This leads to the following condition $\pi(x_i; \beta_H, \alpha_H) - \pi(x_i; \beta_L, \alpha_L) > 0$, $\forall x_i \in (0, 1]$. This is equivalent to $-(\alpha_H - \alpha_L)x_i^2 + p(\beta_H - \beta_L)x_i > 0 \, \forall x_i \in (0, 1]$ or we have $(-(\alpha_H - \alpha_L)x_i^2 + p(\beta_H - \beta_L))x_i > 0$. For all $x_i \in (0, 1]$), the condition requires $-(\alpha_H - \alpha_L)x_i + p(\beta_H - \beta_L) > 0$. Then we have:

- If $\alpha_H < \alpha_L$, then $-(\alpha_H - \alpha_L) > 0$, $-(\alpha_H - \alpha_L)x_i + p(\beta_H - \beta_L)$ presents a line increasing in $(0, 1]$. When the $x_i \to 0$, $-(\alpha_H - \alpha_L)x_i + p(\beta_H - \beta_L) \to p(\beta_H - \beta_L)$. To have the profit under (β_H, α_H) is always higher than profits under (β_L, α_L), then $p(\beta_H - \beta_L) \geq 0$ and $p > 0$, then we only need $\beta_H > \beta_L$.
- If $\alpha_H > \alpha_L$, then $-(\alpha_H - \alpha_L) < 0$, $-(\alpha_H - \alpha_L)x_i + p(\beta_H - \beta_L)$ presents a line decreasing in $(0, 1]$. The point $x_i = 1$ maps to the lowest value. In this case, it requires that $-(\alpha_H - \alpha_L)x_i + p(\beta_H - \beta_L) > 0$ at $x_i = 1$, or $-(\alpha_H - \alpha_L) + p(\beta_H - \beta_L) >$

0, this leads to $p(\beta_H - \beta_L) > \alpha_H - \alpha_L$.

The second condition is that the farmer's total income is non-negative at $x_i = 0$, so they can stay on the conventional method as a status quo. The condition requires $b - c > 0$, so $b > c$.

In the model, we put a condition on the leader's profit function such that $\pi(x_l; \beta_H, \alpha_H) > \pi(x_l; \beta_L, \alpha_L) > \pi(x_l = 0)$ so that leader constantly converses to organic agriculture. The subsidy needs to satisfy $s_l > b - 2c - p\beta_L$. However, we do not constrain the relationship follower's income with and without organic practice so that $\pi(x_f; \beta_i, \alpha_i) - \pi(x_f = 0)$ can take any sign.

We assume that the farmer's preferences follow the axioms of Von Neumann and Morgenstern (2007). This assumption allows that the farmer's preference satisfies the von Newmann-Morgensten expected utility function: $U(\pi)$ is continuous in π, $U'(\pi) > 0, U(0) = 0$. The risk-attitude of farmers is represented by the constant relative risk-aversion utility, which is a utility function used frequently for analyzing farmers' behaviors under risky decisions (Bougherara et al., 2017; Chakravarty and Roy, 2009).

Let $U^i(\pi(x_i)) = \frac{1}{r_i}\pi(x_i)^{r_i}$ when $r_i \neq 0$, and equals $\ln(\pi(x_i))$, when $r_i = 0$, and $U^i(0) = 0$, $i \in \{l, f\}$. Parameter r_i captures the attitude toward risk of farmer i such that:

- $r_i = 1$: risk neutral
- $r_i < 1$: risk aversion
- $r_i > 1$: risk seeking

We assume that the leader and follower's objective is to achieve the maximum utility from the land allocation to agricultural activities in three scenarios:

S1. Leader and farmer know the true state of organic technology (α, β)

S2. Leader knows the true state of organic technology (α, β), but follower does not. Two farmers do not exchange information through a negotiation process.

S3. Leader knows the true state of organic technology (α, β), but follower does not. Two farmers can exchange information through a negotiation process.

3.2.2 Symmetric and complete information

In this scenario, the leader and follower know the actual state of organic technology. The leader decides their allocation x_l first.

Leader's decision

After determining the state of organic technology, the leader's objective is to have the highest utility. Thus, they choose x_l such that

$$x_l \in \underset{0 \le x_l \le 1}{\operatorname{argmax}} U^l(\pi(x_l)) \tag{3.2}$$

For detail, we expand (3.2) to

$$x_l \in \underset{0 \le x_l \le 1}{\operatorname{argmax}} \frac{1}{r_l}(\pi(x_l))^{r_l} \tag{3.3}$$

We take the first derivative of the objective function with respect to π_l

$$\frac{dU^l}{d_{\pi_l}} = \pi(x_l)^{r_l - 1} \tag{3.4}$$

From our setting on the technologies, the first derivative of the objective function is positive for $\pi(x_l) \ge 0$, then the utility is a non-decreasing function on $\pi(x_l)$. Besides, the leader's utility does not include the follower's decision. Thus, the leader's optimal choice is equivalent to the choice such that

$$x_l \in \underset{0 \le x_l \le 1}{\operatorname{argmax}} \pi(x_l) \tag{3.5}$$

Theoretical prediction 3.2.1. *If leader decides their allocation following the equation (3.3) and the assumptions in section 3.2.1 hold, then our model predicts that*

1. *Suppose that the true state is* (β_H, α_H)*, then leader decides*

$$x_l^{s_1} = \begin{cases} \frac{p\beta_H + s_l - b + 2c}{2(\alpha_H + c)}, & \mathit{if}\ \frac{b-2c-s_i}{\beta_H} < p < \frac{b+2\alpha_H - s_l}{\beta_H} \\ 1, & \mathit{if}\ p \geq \frac{b+2\alpha_H - s_l}{\beta_H} \end{cases} \tag{3.6}$$

2. *Suppose that the true state is* (β_L, α_L)*, then leader decides*

$$x_l^{s_1} = \begin{cases} \frac{p\beta_L + s_l - b + 2c}{2(\alpha_L + c)}, & \mathit{if}\ \frac{b-2c-s_f}{\beta_L} < p < \frac{b+2\alpha_L - s_f}{\beta_L} \\ 1, & \mathit{if}\ p \geq \frac{b+2\alpha_L - s_f}{\beta_L} \end{cases} \tag{3.7}$$

Proof. The proof is in Appendix 3.5.1.

□

Follower's decision

The follower observes the leader's decision $x_l^{s_1}$. In this scenario, the follower also knows the actual state of organic technology, and their utility function and income function do not include the leader's decision variable: the leader's decisions do not change the follower's utility, given the follower's decisions. In this sense, the follower decides independently with the leader. Like the leader's decision, the follower decides to get the highest income from land allocation.

$$x_f \in \underset{0 \leq x_f \leq 1}{\operatorname{argmax}}\ \pi(x_f) \tag{3.8}$$

Theoretical prediction 3.2.2. *If the follower decides their allocation following the equation (3.8) and the conditions in section 3.2.1 hold, then our model predicts that the follower's allocation is the same as the leader's allocation such that*

1. *Suppose that the true state is* (β_H, α_H)*, then follower decides*

$$x_f^{s_1} = \begin{cases} 0, & \mathit{if}\ p \leq \frac{b-2c-s_f}{\beta_H} \\ \frac{p\beta_H + s_f - b + 2c}{2(\alpha_H + c)}, & \mathit{if}\ \frac{b-2c-s_f}{\beta_H} < p < \frac{b+2\alpha_H - s_f}{\beta_H} \\ 1, & \mathit{if}\ p \geq \frac{b+2\alpha_H - s_f}{\beta_H} \end{cases} \tag{3.9}$$

2. *Suppose that the true state is* (β_L, α_L), *then follower decides*

$$x_f^{s_1} = \begin{cases} 0, & \text{if } p \leq \frac{b-2c-s_f}{\beta_L} \\ \frac{p\beta_L+s_f-b+2c}{2(\alpha_L+c)}, & \text{if } \frac{b-2c-s_f}{\beta_L} < p < \frac{b+2\alpha_L-s_f}{\beta_L} \\ 1, & \text{if } p \geq \frac{b+2\alpha_L-s_f}{\beta_L} \end{cases} \tag{3.10}$$

Proof. The follower's income function is $\pi_{x_f} = -(\alpha_k+c)x_f^2+(p\beta_k+s_f+b-2c)x_f+b-c$. This income function is identical to the leader's if both farmers allocate the same amount of land to organic agriculture. Then, we follow the same analysis shown in the leader's decision 3.2.2. We have the maxima solution

$$x_f^{s_1} = \frac{p\beta_k + s_f - b + 2c}{2(\alpha_k + c)} \tag{3.11}$$

Leader and follower face the same conditions in section 3.2.1, and then we come to the prediction. □

The optimal allocations of followers differ from the leader's in that the leader always chooses $x_l > 0$ because they receive a subsidy large enough to convert to organic agriculture. However, the followers' subsidy may not guarantee their adoption will always be better than staying in conventional agriculture.

3.2.3 Asymmetric information, without bargaining

This section's situation is the same as that in the first scenario. The one change is that only the leader knows the true state of organic technology at the beginning; the follower does not; the follower could receive information about the leader's decision as in the previous case.

Leader's decision

Under this scenario, the leader's choice is the same as the leader's decision under the first scenario, which we have analyzed above. Let $x_l^{s_2}$ be the leader's choice in this scenario.

Theoretical prediction 3.2.3. *In this scenario, the leader's decision is the same as the decision in the previous Scenario in Section 3.2.2 such that* $x_l^{s_2} = x_l^{s_1}$.

Proof. In this scenario, the leader has the same income function as in (3.1) and also knows the actual state of organic technology (β, α); the leader's choice from this Scenario does not differ from the ones in the Scenario 1. □

Follower's decision

Follower observes the leader's decision, $x_l^{s_2}$ before they make their own decision. We have that $s_l \neq s_f$, and there are no restrictions on s_f such that $\pi(x_f, \alpha_i, \beta_i) > \pi(x_f = 0)$ to guarantee that the follower is better off as they follow leader's allocation. Thus, follower still decides under risk although knowing the leader's decision.

We suppose that the objective probabilities of $(\beta, \alpha) = (\beta_H, \alpha_H)$ is τ and that $(\beta, \alpha) = (\beta_L, \alpha_L)$ is $1 - \tau$; they are a common knowledge. Follower's decision follows

$$x_f \in \underset{0 \leq x_f \leq 1}{\operatorname{argmax}} \, EU(\pi(x_f), \tau) \tag{3.12}$$

For more detail, we expand the equation (3.12):

$$x_f \in \underset{0 \leq x_f \leq 1}{\operatorname{argmax}} \, \frac{1}{r_f}(\tau(\pi(x_f; \alpha_H, \beta_H))^{r_f} + (1 - \tau)(\pi(x_f; \alpha_L, \beta_L))^{r_f}) \tag{3.13}$$

Theoretical prediction 3.2.4. *If the follower maximizes the equation (3.13) in their decision and* $s_l \neq s_f$*, our model predicts that there exists the optimal choice such that*

1. *Risk-neutral follower,* $r_f = 1$*, decides at*

$$x_{f,neu}^{s_2} = \frac{p[\tau\beta_H + (1 - \tau)\beta_L] + s_f - b + 2c}{2[\tau\alpha_H + (1 - \tau)\alpha_L + c]} \tag{3.14}$$

2. *Risk-averse follower,* $r_f < 1$*, decides at*

$$x_{f,ra}^{s_2} = \frac{p[\tau\beta_H + (1 - \tau)\beta_L] + s_f - b + 2c}{2[\tau\alpha_H + (1 - \tau)\alpha_L + c]} + \frac{Cov(U_\pi, -2\alpha x_{f,ra}^{s_2} + p\beta)}{2(\bar{\alpha} + c)} \tag{3.15}$$

3. *Risk-seeking follower, $r_f > 1$, decides such that*

$$x^{s_2}_{f,rs} = \frac{p[\tau\beta_H + (1-\tau)\beta_L] + s_f - b + 2c}{2[\tau\alpha_H + (1-\tau)\alpha_L + c]} + \frac{Cov(U_\pi, -2\alpha x^{s_2}_{f,rs} + p\beta)}{2(\bar{\alpha} + c)} \tag{3.16}$$

Proof. The proof is in Appendix 3.5.2. □

We prove that a follower's decision depends on the probabilities of organic technology and the level of attitude toward risk. We further predict that risk-averse followers are more conservative than risk-neutral, so they may allocate less land to organic agriculture than the choice risk-neutral, given that the two types have the same other factors. The formal prediction is as follows:

Theoretical prediction 3.2.5. *Given that the follower decides following the Prediction (3.2.4), then risk-averse followers allocate less land to organic agriculture than risk-neutral followers, equivalent to $x^{s_2}_{f,ra} < x^{s_2}_{f,neu}$.*

Proof. The proof is in Appendix 3.5.3.

□

Risk-averse farmers constrain their land for organic agriculture because of the risk factors in their final income. However, a subsidy s_f from the government impacts the adoption level. An effect of subsidy change on the utility is represented by $\frac{\delta U}{\delta s_f} = \frac{\delta U}{\delta \pi(x_f)} \frac{\delta \pi(x_f)}{\delta s_f} = \tau[\pi(x_f; \alpha_H, \beta_H)^{r_f - 1}] + (1-\tau)[\pi(x_f; \alpha_L, \beta_L)^{r_f - 1}] > 0$. This subsidy favors the adoption level.

We further analyze the risk-averse farmer's behavior under a subsidy. Recall the their choice is as in result 3.15, then the effect or both risk and subsidy represent in the amount $\frac{Cov(U_\pi, -2\alpha x^{s_2}_{f,ra} + p\beta)}{2(\bar{\alpha}+c)}$ and from the Appendix 3.5.2, we obtain that $Cov(U_\pi, -2\alpha x^{s_2}_{f,ra} + p\beta) = \tau(1-\tau)(-2(\alpha_H - \alpha_L)x^{s_2}_f + p(\beta_H - \beta_L))\Delta U_\pi$, where $\Delta U_\pi = U_\pi(x^{s_2}_f; \alpha_H, \beta_H) - U_\pi(x^{s_2}_f; \alpha_L, \beta_L)$. The effect of subsidy comes from the ΔU_π such that.

$$\frac{\delta \Delta U_\pi}{\delta s_f} = x_f(r_f - 1)[\pi(x_f; \alpha_H, \beta_H)^{r_f - 2} - \pi(x_f; \alpha_L, \beta_L)^{r_f - 2}] \tag{3.17}$$

For a risk-averse farmers, $r_f < 1$, then $r_f - 1 < 0$, and $x_f > 0$ the sign of representation above is opposite the sign of $[\pi(x_f; \alpha_H, \beta_H)^{r_f-2} - \pi(x_f; \alpha_L, \beta_L)^{r_f-2}]$. We have $\pi(x_f; \alpha_H, \beta_H) > \pi(x_f; \alpha_L, \beta_L)$, and $r_f - 2 < 0$, then $\pi(x_f; \alpha_H, \beta_H)^{r_f-2} - \pi(x_f; \alpha_L, \beta_L)^{r_f-2} < 0$. This leads to $\frac{\delta \Delta U_\pi}{\delta s_f} > 0$: the adoption level of risk-averse farmer increases as the subsidy rises.

For a risk-neutral farmer, $r_f = 1$, then $\frac{\delta \Delta U_\pi}{\delta s_i} = 0$: the subsidy does not change the optimal adoption level of the risk-neutral farmer. For a relatively low level of risk-loving farmers, $1 < r_f \leq 2$, we observe that an increase in subsidy reduces the effect of risk on those farmers: their land investment tends to the level of risk-neutral farmers as s_f is bigger. However, for higher risk-loving levels, $r_f > 2$, then $\frac{\delta \Delta U_\pi}{\delta s_f} > 0$: those farmers react to an increasing subsidy by augmenting their land allocation toward organic agriculture.

3.2.4 Asymmetric information with bargaining

We extend the model in the previous section by considering that leaders can inform followers of the true state of organic technology so that followers maximize their payoffs after knowing the full information. To create monetary incentives for this diffusion, we base on Nash's bargaining model: farmers negotiate to share information and share the gain if the information creates a higher profit for the follower.

Before bargaining, the leader and follower decide if they fail to cooperate, and the leader does not inform the follower. We use the variable disagreement points defined in Nash (1953) such that farmers' decisions are in Section 3.2.3. In more details, leader allocates x_l^d such that

$$x_l^d \in \underset{0 \leq x_l \leq 1}{\operatorname{argmax}} -(\alpha + c_l)x_l^2 + (p\beta + s_l - b_l + 2c_l)x_l + b_l - c_l \tag{3.18}$$

And leader chooses x_l^d, farmer observes x_l^d. We consider the same situation as in Scenario 2: The farmer knows x_l^d and chooses the disagreement point as

$$x_f^d \in \underset{0 \leq x_f \leq 1}{\operatorname{argmax}} EU^f(\pi^f(x_f)) = \frac{1}{r_f}(\tau \pi(x_f; \beta_H, \alpha_H)^{r_f} + (1-\tau)\pi(x_f; \beta_L, \alpha_L)^{r_f}) \tag{3.19}$$

Theoretical prediction 3.2.6. *If leader and follower use equation (3.18) and equation (3.19) to decide their disagreement point respectively and the probabilities of organic technology are kept as in Scenario 2, then they decide as in the Scenario 3.2.3.*

Proof. We quickly see that the problems in equation (3.18) and equation (3.19) are the same as the problem in equation (3.8) in Scenario 1 for the leader and in equation (3.13) in Scenario 2 for the follower, given that the conditions are the same, thus the solutions for disagreement are the solution in Scenario 2. □

In the next step, the leader and follower bargain to agree. To realize this Step, farmers have to know the benefit that they gain with information in (β_H, α_H), denoted G_H, and in (β_L, α_L), denoted G_L. Leader and follower have an incentive to bargain if their incomes from bargaining are higher than their disagreement point; this requires $G_H > 0$ under (β_H, α_H) and $G_L > 0$ under (β_L, α_L)

Collary 3.2.1. *If leader's decision at the point defined in Prediction 3.2.1, and the followers' disagreement choice defined as in equation (3.19), then the benefit from bargaining is positive:* $G_H > 0$ *and* $G_L > 0$.

Proof. The proof is in Appendix 3.5.4.

□

We prove that getting information generates positive benefits, so income with successful bargaining is higher than income without it. Consequently, the follower's utility with bargaining is higher than the one without. On the leader's side, the leader helps the follower by offering accurate information on technology, so the leader has the right to demand a share of the follower's gains. We build a bargaining process to allow for a negotiation on the shares to each farmer as follows:

Step 1: The Leader receives the actual state of organic technology and decides their allocation. The follower observes the leader's decisions and makes their allocation. Two players receive the realized profits. This Task helps farmers calculate the income from the disagreement point and then the gain.

Step 2: Two farmers come to the Bargaining game. Following the Gáfaro and Mantilla (2020) and Duffy et al. (2021), the Bargaining game is designed as

- Farmers know that they can achieve the gain G_k, $k = (H, L)$, then they negotiate on the percentage of G_k.
- Leader sends their demand on the share, denote y_l, to the follower. The share of followers is $1 - y_l$.
- Other farmers accept or reject and send counter-demand s_f.
- Only messages on proposals are allowed.
- The bargaining is limited in time or is ended after a n rounds with defined probability.
- The bargaining ends under one of two conditions comes first:
  - Whenever there all farmers accept a proposal
  - Time is up or ended by probability.

If there is an agreement, the follower knows the information, generates the gains, and shares the agreed part of the gains with the leader. Otherwise, the leader and follower receive the profits, and then utilities are decided in Task 1. The bargaining model follows Nash's bargaining model, and we find a solution to this bargaining problem such that

Theoretical prediction 3.2.7. *Following the bargaining process, our model predicts that $y > 0$. Thus, leaders and followers always get higher utility with bargaining than the utilities with disagreement.*

Proof. The bargaining focuses on the gain's shares, letting y_l and y_f be the leader and follower share, respectively. Follow Nash (1953) and Kalai (1977), the Nash bargaining solution is

$$y_l^a, y_f^a \in \underset{y\in[0,1]}{\text{argmax}}\ y_f^{\theta_f} y_l^{\theta_l} \tag{3.20}$$

$$\text{subject to } y_l + y_f = 1$$

where θ_f is bargaining power of follower and θ_l is for leader. We have the Lagrange function $L = y_f^{\theta_f} s_l^{\theta_l} - \mu(1 - y_l - y_f)$. Taking the FOC such that

$$\frac{\delta L}{\delta y_l^a} = \theta_f y_f^{\theta_f - 1} y_l^{\theta_l} - \mu = 0 \tag{3.21}$$

$$\frac{\delta L}{\delta y_f^a} = \theta_l y_l^{\theta_l - 1} y_f^{\theta_f} - \mu = 0 \tag{3.22}$$

$$\frac{\delta L}{\delta \mu} = 1 - y_l - y_f = 0 \tag{3.23}$$

We have a solution such that

$$y_f^a = \frac{\theta_f}{\theta_f + \theta_l} \tag{3.24}$$

and

$$y_l^a = \frac{\theta_l}{\theta_l + \theta_f} \tag{3.25}$$

Then, the gain after bargaining are $\frac{\theta_f}{\theta_f+\theta_l} G_k$ for follower and $\frac{\theta_l}{\theta_l+\theta_f} G_k$ for leader. The leader's utility after bargaining is $U^l\left(\pi(x_l^d) + \frac{\theta_l}{\theta_l+\theta_f} G_k\right) > U^l(x_l^d)$; follower's utility after bargaining is $U^f\left(\pi(x_l^d) + \frac{\theta_f}{\theta_f+\theta_l} G_k\right) > U^f(x_f^d)$. Leaders and followers are better at bargaining than without bargaining.

$\square$

Our model has proved that leaders and followers receive higher income by bargaining. Those higher incomes are the incentive that the leaders and followers want to negotiate.

3.3 Model parameterization

In this section, we choose to fit the numerical values of conventional and organic technology. The empirical results from Crowder and Reganold (2015) and Seufert et al. (2012) show that

- The conventional yield is usually higher than the organic yield. However, best organic practices can obtain higher yields.
- Farmers save the cost of reducing the pesticides and fertilizer under organic agriculture, but they have to put more labor costs than in conventional agriculture. Thus, the organic cost may be high initially and then lower.
- The organic price is higher than the conventional price.

We build a scenario in which leaders always converse about organic agriculture, and followers only converse if organic technology is in a high state.

We also refer to rice production in Vietnam and modify our experiment properly. Thus, the parameters are as follows:

- Conventional agriculture:
  - Conventional technology: $b = 6$ tons per land hectares; $c = 2$ ECUs *(experimental currency units)* per hectares
  - Conventional price is normalized to 1
- The organic product price is higher than the conventional one, we set $p = 1.4$
- If the true state is high organic technology, then farmers allocate 0.8 land to organic agriculture. Thus, we choose $\alpha_H = 2$, we choose
$$\beta_H = \frac{2 * 0.7(\alpha_H + c) + b - 2c}{p} = 4 \tag{3.26}$$
- Farmers do not allocate land to organic agriculture if the true state is low organic technology. We suppose low technology has higher organic cost $\alpha_L = 2.5$, then we choose $\beta_L = 0.65$

- The subsidy that guarantee that leader always converse has to greater than 1.09, so we choose subsidy for leader is $s_l = 2$ and for follower. We set up a scenario in which the follower will adopt organic agriculture under high organic technology and not adopt under low organic technology, so we choose $s_f = 1$

Under those settings, the income function for leaders under high organic productivity is such that.

$$\pi(x_i) = -4x_l^2 + 5.6x_l + 4 \tag{3.27}$$

At the low productivity:

$$\pi(x_i) = -4.5x_l^2 + 0.91x_l + 4 \tag{3.28}$$

The income function of followers at high organic technology

$$\pi(x_i) = -4x_f^2 + 4.6x_f + 4 \tag{3.29}$$

At the low productivity:

$$\pi(x_i) = -4.5x_f^2 - 0.09x_f + 4 \tag{3.30}$$

S1: All farmers know the true state

If the true state is the high organic technology $(\beta_H, \alpha_H) = (4, 2)$ then leader decides at

$$x_l^{s_1} = \frac{5.6}{2 * 4} = 0.7 \tag{3.31}$$

Leader invests 70 percent of their land in organic agriculture and receives corresponding income is $\pi(x_l^{s_1}) = 5.96$ ECUs. Meanwhile, followers will invest 57.5 percent of their land. The lower allocation can be explained by the lower government's received. The follower's income, in this case, is 5.3225 ECUs.

If they know that the state is in the $(\beta_L, \alpha_L) = (1.97, 1.62)$, then

$$x_l^{s_1} = x_f^{s_1} = \frac{1.76}{2 * 4.4} = 0.2 \tag{3.32}$$

If the true state is at the low organic technology $(\beta_L, \alpha_L) = (2.5, 0.65)$, then the leader allocates 10.1 percent of lands to organic agriculture and gets 4.06 ECUs. This allocation is supported completely by a subsidy $s_l = 2$. Without subsidy, the leader's income is lower than staying on conventional agriculture to get 4 ECUs. Our models show that the follower stays in conventional agriculture and receives 4 ECUs. We illustrate leader allocation as in the following Figure 3.1, and follower's allocation is represented in Figure 3.2

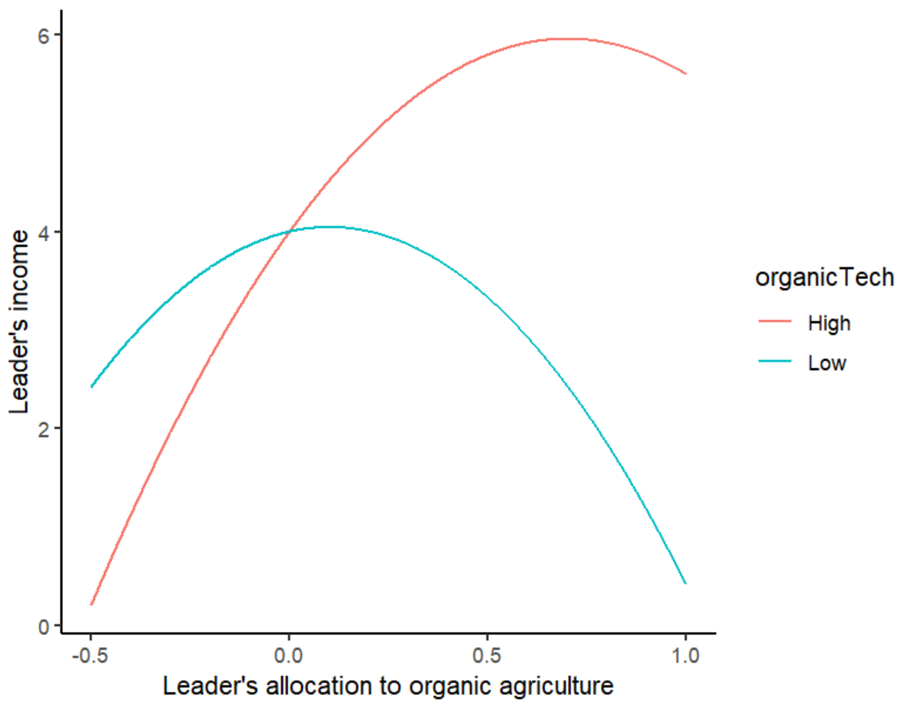

Figure 3.1: Leader's land allocation and total profit in scenario 1

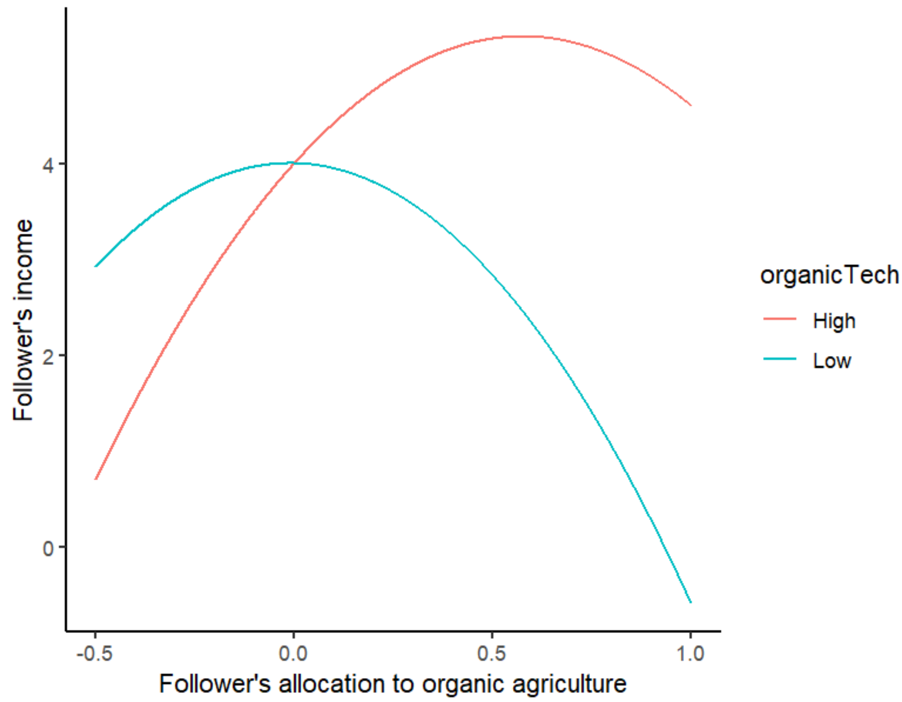

Figure 3.2: Follower's land allocation and total profit in scenario 1

S2: Only leader has information, without bargaining

In this scenario, our model predicts that the leader decides the same as in Scenario 1. If the state is for high organic technology and low technology, thus we have $x_l^{s_2} = x_l^{s_1} = 0.7$ and receive profit $\pi(x_l^{s_2}; \beta_H, \alpha_H) = 5.96$ ECUs. At the low organic technology, we have $x_l^{s_2} = x_l^{s_1} = 0.101$, they get $\pi(x_l^{s_2}; \beta_L, \alpha_L) = 4.06$ ECUs.

Follower's decision

In scenario 2, our model predicts that follower's decisions depend on their risk attitude. We simulate the change in land allocation by the risk level from -10 to 10 in Figure 3.3. Followers increase their land allocation if they are less risk-averse.

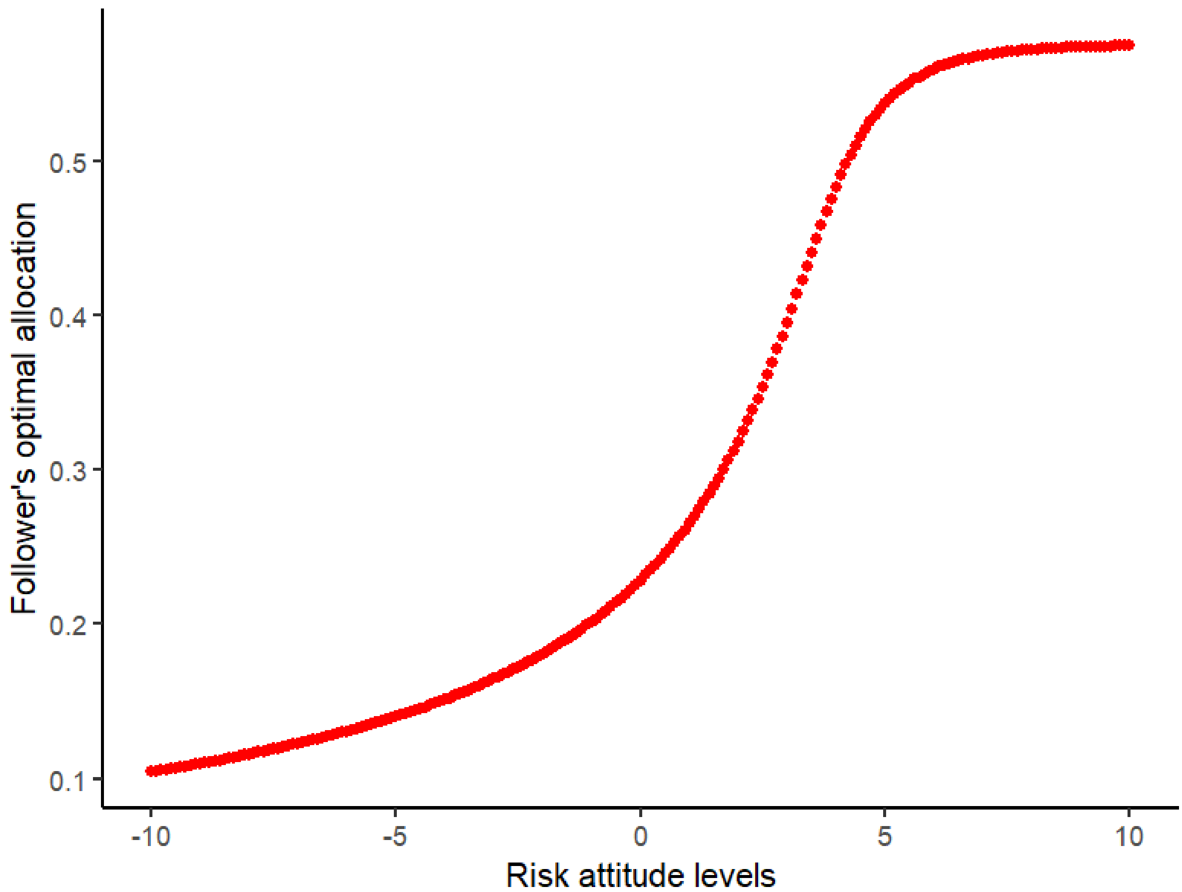

Figure 3.3: Follower optimal land allocation under attitude toward risk in scenario 2

In table 3.1, we set the risk level at -4 for risk-averse, 1 for risk-neutral, and 4 for risk-loving followers and calculate their corresponding adoption level and profit.

Table 3.1: The allocation of land: Only leaders know the true state, no bargaining

	Risk averse	**Risk-neutral**	**Risk-seeking**
Allocation (x_f)	**0.15**	**0.26**	**0.48**
Realized tech	HIGH	HIGH	HIGH
Realized profit	4.6	4.93	5.28
Allocation if knowing information	0.575	0.575	0.575
Income if knowing yield	5.32	5.32	5.32
Realized tech	LOW	LOW	LOW
Realized profit	3.88	3.65	2.90
Allocation if knowing information	0	0	0
Income if knowing yield	4	4	4

S3: Only the leader knows the information, with bargaining

Our model predicts that the leader and follower choose the disagreement allocation such that as in scenario 2

- $x_l^d = x_l^{s_2}$
- $x_f^d = x_f^{s_2}$

Followers do not know the information, so they choose under risk. The follower receives information about the leader's choice and decides, as in Scenario 2.

Leader and follower bargain to share the G: leader receives s_l, and follower receives s_f. We summarize the results in the Table 3.2

Table 3.2: The allocation of land: Only leaders know the true state, bargaining

	Risk averse	**Risk-neutral**	**Risk-seeking**
Allocation (x_f)	**0.15**	**0.26**	**0.48**
Realized tech	HIGH	HIGH	HIGH
Realized profit (1)	4.6	4.93	5.28
Allocation if knowing information	0.575	0.575	0.575
Income if knowing yield (2)	5.32	5.32	5.32
Bargaining gain $G_H = (2) - (1)$	0.72	0.39	0.04
Share (s_l^H, s_f^H)	$(0.36, 0.36)$	(0.195,0.195)	(0.02,0.02)
Final income (π_l^a, π_f^a)	(6.32, 4.96)	(6.155, 5.125)	(5.98, 5.3)
Realized tech	LOW	LOW	LOW
Realized profit (3)	3.88	3.65	2.90
Allocation if knowing information	0	0	0
Profit if knowing yield (4)	4	4	4
Bargaining gain $G_L = (4) - (3)$	0.12	0.35	1.1
Share $(s_l^L, s_f^L) = G/2$	$(0.06, 0.06)$	(0.175,0.175)	(0.55,0.55)
Final income (π_l^a, π_f^a)	(4.14, 3.94)	(4.215, 3.71)	(4.59, 3.45)

Note: we calculate $\pi_l^a = (2) + s_l^H$ and $\pi_f^a = (1) + s_f^H$ for HIGH; $\pi_l^a = (4) + s_l^L$ and $\pi_f^a = (3) + s_f^L$ for LOW.

3.4 Conclusion

Transitioning to organic agriculture is crucial for the well-being of farmers, consumers, and the environment. Studies have shown that such a shift can have numerous benefits, including promoting biodiversity, mitigating climate change, sustaining ecosystems, and safeguarding human health (Seufert et al., 2012). However, despite these advantages, adopting organic farming has not met the desired expectations, and farmers face several challenges when choosing.

Our study focuses on the risks that farmers face when deciding to adopt organic agriculture. We analyze the risks associated with incomplete information about production methodologies, precisely, the two states of organic return.

We propose a solution where farmers can exchange information to improve their understanding of the benefits and risks associated with organic farming before deciding. Our theoretical model demonstrates that farmers' decisions are influenced by their attitudes toward risks, and our Nash-bargaining game shows that farmers are willing to exchange bargaining gains to obtain additional information.

Our study suggests that providing farmers with information is essential to help them overcome their fears and promote adopting organic agriculture. However, our model focuses on the role of "informal leaders" who have access to information before other farmers. We suggest these informal leaders can be focal points to disseminate information across networks, as discussed in Beaman et al. (2021).

3.5 Supporting information

3.5.1 Proof of prediction 3.2.1

Proof. We know that $\pi(x_l) = -(\alpha + c)x_l^2 + (p\beta + s_l - b + 2c)x_l + b - c$; the FOC is

$$-2(\alpha + c)x_l^{s_1} + (p\beta + s_l - b + 2c) = 0$$

From that, we have unconstrained optimal $x_l^{s_1} = \frac{(p\beta_k + s_l - b + 2c)}{2(\alpha_k + c)}$, where $k = (H, L)$. Then, the the SOC is $-2(\alpha_k + c) < 0$, $\forall x_l \in [0, 1]$. Then, $x_l^{s_1}$ is the maxima that gives the leader the highest income and utility. We will consider the corner solutions:

If $p \leq \frac{b - 2c - s_l}{\beta_k}$, then $x_l^{s_1}(\beta_k, \alpha_k) \leq 0$. This also leads to the decrease in objective function at 0: the more land for organic agriculture a leader receives, the lesser the income. Thus, leader chooses $x_l^{s_1}(\beta_k, \alpha_k) = 0$: they do not adopt to organic agriculture.

If $p \geq \frac{b + 2\alpha_k - s_f}{\beta_k}$. This implies that the first derivative $-2(\alpha_k + c)x_l^{s_1} + (p\beta_k + s_l - b + 2c) > 0$ at $x_l^{s_1}(\beta_k, \alpha_k) = 1$, then the leader's income still increases at $x_l^{s_1}(\beta_k, \alpha_k) = 1$, but they are constrained by the land: they choose $x_l^{s_1}(\beta_k, \alpha_k) = 1$.

□

3.5.2 Proof of theoretical prediction 3.2.4

Proof. The optimal choice $x_f^{s_2}$ satisfies the FOC such that

$$E[U_\pi \pi_{x_f}(x_f^{s_2})] = 0 \tag{3.33}$$

where $U_\pi = (\pi(x_f^{s_2}; \alpha, \beta))^{r_f - 1}$ and $\pi_{x_f}(x_f^{s_2}) = -2(\alpha + c)x_f^{s_2} + p\beta + s_f - b + 2c$ is the first derivative of π_{x_f} at $x_f^{s_2}$. Equation (3.33) is rewritten as

$$\begin{aligned} & E[U_\pi(-2\alpha x_f^{s_2} + p\beta + s_f - 2cx_f^{s_2} - b + 2c)] = 0 \\ \iff & E[U_\pi(-2\alpha x_f^{s_2} + p\beta)] + (-2cx_f^{s_2} + s_f - b + 2c)E[U_\pi] = 0 \end{aligned} \tag{3.34}$$

Firstly, we have the property that $E[U_\pi(-2\alpha x_f^{s_2} + p\beta)] = Cov(U_\pi, -2\alpha x_f^{s_2} + p\beta) + E[U_\pi]E[-2\alpha x_f^{s_2} + p\beta]$. Then, the second expectation on the right-hand side is

$$\begin{aligned} E[-2\alpha x_f^{s_2} + p\beta] &= \tau(-2\alpha_H x_f^{s_2} + p\beta_H) + (1-\tau)(-2\alpha_L x_f^{s_2} + p\beta_L) \\ &= -2(\tau\alpha_H + (1-\tau)\alpha_L)x_f^{s_2} + p(\tau\beta_H + (1-\tau)\beta_L) \\ &= -2\bar{\alpha}x_f^{s_2} + p\bar{\beta} \end{aligned} \tag{3.35}$$

where $\bar{\alpha} = \tau\alpha_H + (1-\tau)\alpha_L$ and $\bar{\beta} = \tau\beta_H + (1-\tau)\beta_L$. The income $\pi(x_f^{s_2}; \beta_H, \alpha_H) > 0$ and $\pi(x_f^{s_2}; \beta_L, \alpha_L) > 0$, then $E[U_\pi] = \tau\pi(x_f^{s_2}; \beta_H, \alpha_H)^{r_l - 1} + (1-\tau)\pi(x_f^{s_2}; \beta_L, \alpha_L)^{r_l - 1} > 0$, we divide two sides of equation (3.34) by $E[U_\pi]$ and rearrange to obtain

$$-2(\bar{\alpha} + c)x_f^{s_2} + p\bar{\beta} + s_f - b + 2c + \frac{Cov(U_\pi, -2\alpha x_f^{s_2} + p\beta)}{E[U_\pi]} = 0 \tag{3.36}$$

Next, we take the second-order condition of the optimal problem are

$$\frac{dU^2(\pi(x_f^{s_2}))}{dx_f^{s_2}dx_f^{s_2}} = \underbrace{(r_i - 1)E[U^i_{\pi\pi}(\pi(x_f^{s_2}))(\pi_x(x_f^{s_2}))^2]}_{\text{depend on the attitude toward risk}} - \underbrace{2E[U^i_\pi(\pi(x_f^{s_2}))(c + \alpha)]}_{>0} \tag{3.37}$$

If farmers are risk-neutral, $r_f = 1$, or risk-averse, $r_f < 1$, then the second order condition in equation (3.36) is negative for all x_f. Then, the implicit function $F(x_f^{s_2}, \alpha, \beta, c, b, p, r_f) = 0$ in equation (3.36) satisfies the Implicit function theorem. Thus, there exists a function that $x_f^{s_2} = \phi(\alpha, \beta, c, b, p)$ is the maximized allocation of risk-neutral and risk-averse farmers.

For the risk-neutral farmer, they have $r_f = 1$, then $U_\pi = (\pi(x_f^{s_2}; \alpha, \beta))^0 = 1$. This makes $Cov(U_\pi, -2\alpha x_f^{s_2} + p\beta) = Cov(1, -2\alpha x_f^{s_2} + p\beta) = 0$ because covariance between constant and random variables is zero. Then from equation (3.36), risk-neutral follower decides

$$x_{f,neu}^{s_2} = \frac{p\bar{\beta} + s_f - b + 2c}{2(\bar{\alpha} + c)} \tag{3.38}$$

For risk-averse follower, we rearrange equation (3.36) such that the risk-averse farmer's choice satisfies

$$x^{s_2}_{f,ra} = \frac{p\bar{\beta} + s_f - b + 2c}{2(\bar{\alpha} + c)} + \frac{Cov(U_\pi, -2\alpha x^{s_2}_{f,ra} + p\beta)}{2(\bar{\alpha} + c)}$$

If farmers are risk-seeking, $r_f > 1$, the utility function is a convex function in π; $\pi(x_f)$ is a concave function in x_f, then the second derivative of risk-seeking follower's utility may be positive or negative depending on the degree of risk-seeking.

- If equation (3.37) is negative and $r_f > 1$, $x^{s_2}_f$ is the allocation that gives the highest expected utility to a risk-seeking follower:

$$x^{s_2}_{f,rs} = \frac{p\bar{\beta} + s_f - b + 2c}{2(\bar{\alpha} + c)} + \frac{Cov(U_\pi, -2\alpha x^{s_2}_{f,rs} + p\beta)}{2(\bar{\alpha} + c)}$$

- If equation (3.37) is positive and $r_f > 1$, $x^{s_2}_f$ is the allocation $x^{s_2}_{f,rs}$ that gives the lowest expected utility to risk-seeking farmers in the interval $[0, 1]$.

$\square$

3.5.3 Proof of prediction 3.2.5

Proof. Both objective functions of risk-averse and risk-neutral followers are continuous and concave in x_f, and the second derivative in equation (3.37) is negative in the interval $[0, 1]$. There exist global maxima for risk-averse at $x^{s_2}_{f,ra}$ at which the first derivative in equation (3.36) satisfies. To be the global maxima, this is necessary that allocation in first derivative in equation (3.36) is positive for any $x^{s_2}_f \in [0, x^{s_2}_{f,ra})$ and negative for any $x^{s_2}_f \in (x^{s_2}_{f,ra} 1]$. We calculate the first derivative of the risk-averse follower at the choice of risk-neutral follower, $x^{s_2}_{f,neu}$ such that

$$\begin{aligned}\frac{dF(x^{s_2}_{f,neu}; r_f < 1)}{dx^{s_2}_{f,neu}} &= -2(\bar{\alpha}+c)x^{s_2}_{f,neu} + p\bar{\beta} + s_f - b + 2c + \frac{Cov(U_\pi, -2\alpha x^{s_2}_{f,neu} + p\beta)}{E[U_\pi]} \\ &= -2(\bar{\alpha}+c)\frac{p\bar{\beta} + s_f - b + 2c}{2(\bar{\alpha}+c)} + p\bar{\beta} - b + 2c + \frac{Cov(U_\pi, -2\alpha x^{s_2}_{f,neu} + p\beta)}{E[U_\pi]} \\ &= \frac{Cov(U_\pi, -2\alpha x^{s_2}_{f,neu} + p\beta)}{E[U_\pi]} \end{aligned} \tag{3.39}$$

We further obtain the expression of the covariance element in the equation above

$$\frac{Cov(U_\pi, -2\alpha x^{s_2}_{f,neu} + p\beta)}{E[U_\pi]} = \frac{\tau(1-\tau)(-2(\alpha_H - \alpha_L)x^{s_2}_{f,neu} + p(\beta_H - \beta_L))\Delta U_\pi}{\tau U_\pi(x^{s_2}_{f,neu}; \alpha_H, \beta_H) + (1-\tau)U_\pi(x^{s_2}_{f,neu}; \alpha_L, \beta_L)} \tag{3.40}$$

where $\Delta U_\pi = U_\pi(x^{s_2}_f; \alpha_H, \beta_H) - U_\pi(x^{s_2}_f; \alpha_L, \beta_L) = \pi(x^{s_2}_{f,neu}; \beta_H, \alpha_H)^{r_f-1} - \pi(x^{s_2}_{f,neu}; \beta_L, \alpha_L)^{r_f-1}$.

It is that $\pi(x^{s_2}_{f,neu}; \beta_L, \alpha_L) > 0$ and $r_f - 1 < 0$, then $(\pi(x^{s_2}_{f,neu}; \beta_L, \alpha_L))^{r_f-1}$ is a decreasing function. Knowing that the condition in technologies hold, $\pi(x^{s_2}_{f,neu}; \beta_H, \alpha_H) > \pi(x^{s_2}_{f,neu}; \beta_L, \alpha_L) \geq 0$. Thus, $\pi(x^{s_2}_{f,neu}; \beta_H, \alpha_H)^{r_f-1} < \pi(x^{s_2}_{f,neu}; \beta_L, \alpha_L)^{r_f-1}$, thus we have $\Delta U_\pi < 0$.

Next, we calculate the quantity $C = -2(\alpha_H - \alpha_L)x^{s_2}_{f,neu} + p(\beta_H - \beta_L)$ in the covariance such that

$$\begin{aligned}
C &= -2(\alpha_H - \alpha_L)x^{s_2}_{f,neu} + p(\beta_H - \beta_L) \\
&= -(\alpha_H - \alpha_L)\frac{p\bar{\beta} + s_f - b + 2c}{(\bar{\alpha} + c)} + p(\beta_H - \beta_L)
\end{aligned}$$

knowing that $\bar{\beta} = \tau\beta_H + (1-\tau)\beta_H = \tau(\beta_H - \beta_L) + \beta_L$

and $\bar{\alpha} = \tau\alpha_H + (1-\tau)\beta_H = \tau(\alpha_H - \alpha_L) + \alpha_L$ then

$$\begin{aligned}
(\bar{\alpha} + c)C &= -(\alpha_H - \alpha_L)(p\tau(\beta_H - \beta_L) + p\beta_L - b + 2c) \\
&+ p(\tau(\alpha_H - \alpha_L) + \alpha_L + c)(\beta_H - \beta_L) \\
&= -p\tau(\beta_H - \beta_L)(\alpha_H - \alpha_L) - (\alpha_H - \alpha_L)(p\beta_L - b + 2c) + p\tau(\beta_H - \beta_L)(\alpha_H - \alpha_L) \\
&+ p(\alpha_L + c)(\beta_H - \beta_L)
\end{aligned}$$

divide two sides by $(\alpha_L + c)$

$$\frac{(\bar{\alpha} + c)}{\alpha_L + c}C = p(\beta_H - \beta_L) - (\alpha_H - \alpha_L)\frac{p\beta_L + s_f - b + 2c}{2(\alpha_L + c)} \tag{3.41}$$

If $\frac{p\beta_L + s_f - b + 2c}{2(\alpha_L + c)} < 1$ and $p(\beta_H - \beta_L) > (\alpha_H - \alpha_L)$, then $C > 0$.

Finally, the covariance in equation (3.41) is negative. The choice of risk-neutral follower lies in the regions that make the first derivative of the risk-averse function negative, thus $x^{s_2}_{f,ra} < x^{s_2}_{f,neu}$. □

3.5.4 Proof of corollary 3.2.1

Proof. First, we prove that $G_H > 0$. If leader informs that $(\beta, \alpha) = (\beta_H, \alpha_H)$, follower maximizes the utility at

$$x^H_f = \frac{p\beta_H + s_f - b + 2c}{2(\alpha_H + c)} \tag{3.42}$$

As this choice, the corresponding income is

$$\begin{aligned}
\pi(x^H_f) &= -(\alpha_H + c)(x^H_f)^2 + (p\beta_H + s_f - b + 2c)x^H_f + b - c \\
&= \frac{(p\beta_H + s_f - b + 2c)^2}{4(\alpha_H + c)}
\end{aligned} \tag{3.43}$$

We suppose that $x_f^d \neq x_f^H$, then we write $x_f^d = x_f^H + \eta_H$, where $\eta_H \neq 0$. The follower's income as a disagreement point is

$$\begin{aligned}\pi(x_f^d) &= -(\alpha_H + c)(x_f^d)^2 + (p\beta_H + s_f - b + 2c)x_f^d + b - c \\ &= -(\alpha_H + c)(x_f^H + \eta_H)^2 + (p\beta_H + s_f - b + 2c)(x_f^H + \eta_H) + b - c \end{aligned} \tag{3.44}$$

We take the difference between income with information from bargaining and income without bargaining such that

$$\begin{aligned} G_H \equiv \pi(x_f^H) - \pi(x_f^d) &= -(\alpha_H + c)(x_f^H)^2 + (p\beta_H + s_f - b + 2c)x_f^H + b - c - (-(\alpha_H + c)(x_f^H + \eta_H)^2 \\ &\quad + (p\beta_H - b + 2c)(x_f^H + \eta_H) + b - c) \\ &= -(\alpha_H + c)((x_f^H)^2 - (x_f^H + \eta_H)^2) + (p\beta_H + s_f - b + 2c)\eta_H \\ &= \eta_H(\alpha_H + c)(2x_f^H + \eta_H) - (p\beta_H + s_f - b + 2c)\eta_H \\ &= \eta_H^2(\alpha_H + c) + \eta_H((\alpha_H + c)(2x_f^H) - (p\beta_H + s_f - b + 2c)) \\ \text{Replace } x_f^H &= \frac{p\beta_H + s_f - b + 2c}{2(\alpha_H + c)} \text{ we have} \\ &= \eta_H^2(\alpha_H + c) + \eta_H \underbrace{\left((\alpha_H + c)2\frac{p\beta_H + s_f - b + 2c}{2(\alpha_H + c)} - (p\beta_H + s_f - b + 2c)\right)}_{=0} \\ &= \eta_H^2(\alpha_H + c) > 0 \end{aligned} \tag{3.45}$$

Suppose organic technology is (β_L, α_L). Followers choose such that

$$x_f^L = \frac{p\beta_L - b + 2c}{2(\alpha_L + c)} \tag{3.46}$$

As this choice, the corresponding income is

$$\begin{aligned}\pi(x_f^L) &= -(\alpha_L + c)(x_f^L)^2 + (p\beta_L + s_f - b + 2c)x_f^L + b - c \\ &= \frac{(p\beta_L + s_f - b + 2c)^2}{4(\alpha_L + c)} \end{aligned} \tag{3.47}$$

Let $x_f^d = x_f^L + \eta_L$, we also have that $G_L \equiv \pi(x_f^L) - \pi(x_f^d) = \eta_L^2(\alpha_L + c) > 0$.

$\square$

Chapter 4

Nash-bargaining model in organic agriculture's adoption: Lab-in-field experiment in Northern Vietnam

This Chapter is from a paper working under the same name. The co-authors of this paper are:

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Summary

This study examines the influence of information sharing and cooperation among farmers on adopting organic agriculture, utilizing data from a field experiment conducted in northern Vietnam. A lack of information on organic technology hampers land allocation to organic agriculture. Our analysis reveals that farmers engage in cooperative behavior, as evidenced by their willingness to participate in a Nash bargaining model to access information and share benefits. Furthermore, our results support the hypothesis that equal gains are a focal point in cooperative agreements, aligning with theoretical predictions in bargaining theory. Additionally, we highlight the significant impact of non-monetary factors, such as social value orientation, on farmers' decision-making processes. This research provides valuable insights for policymakers seeking to promote information dissemination and facilitate the transition to sustainable agricultural practices.

Keywords: Organic agriculture; Nash bargaining model; Social value orientation.
JEL code: C91, C93, O13, Q12

4.1 Introduction

Organic agriculture offers a solution to mitigate the adverse environmental effects of conventional farming practices. By safeguarding biodiversity, improving soil health, preventing pollution, and adhering to regulatory standards, organic farming promotes both ecological sustainability and the well-being of farmers (Eyhorn et al., 2019; Reganold and Wachter, 2016). Consequently, adopting organic techniques fosters sustainable agriculture and addresses environmental degradation.

In the last two decades, organic farming has gained traction worldwide, with 188 countries collectively cultivating approximately 96.4 million hectares of organic agricultural land, an exponential increase from the 15 million hectares recorded in 2000 (Willer et al., 2024). Despite this global trend, organic agriculture in Vietnam remains relatively modest, accounting for only 2.2 percent of the country's total agricultural land, encompassing approximately 230,000 hectares. Farmers face challenges transitioning to organic practices, primarily stemming from yield fluctuations (Reganold and Wachter, 2016). Organic farming poses more significant productivity risks than conventional farming due to lower and more variable yields (Knapp and van der Heijden, 2018; Seufert et al., 2012; Wittwer et al., 2021). Moreover, studies have shown that organic agriculture's perceived economic benefits, including premium prices and externalities, influence farmers' decision-making processes (Chèze et al., 2020b; Crowder and Reganold, 2015). Consequently, risk-averse farmers refer to conventional agriculture, causing a low rate of the adoption of organic practices (Chèze et al., 2020b). Additionally, the prevalence of small-scale farming in Vietnam exacerbates this reluctance to adopt new methods, as farmers prioritize income stability over potential gains from organic premiums, which may not be as reliable as those in developed countries (Jouzi et al., 2017).

Our study proposes a potential solution to the above problem by proposing the Nash-bargaining model as a mechanism for farmer cooperation in adopting organic agriculture. The lab-in-field experiment provides insight into evaluating the model's propositions so that policymakers and relevant stakeholders can use those recommendations in their projects promoting organic agriculture.

Firstly, the model focuses on production risk—the uncertainty in productivity that impacts farmers' income (Bontemps et al., 2021). Lack of experience in organic farming exacerbates this risk. Therefore, the diffusion of information about organic agriculture enriches farmers' knowledge and know-how, facilitating their transition to new methodologies. Empirical evidence supports the positive impact of information diffusion on farmers' decision-making, as demonstrated by increased adoption rates observed in randomized controlled experiments (BenYishay and Mobarak, 2019). Farmers rely on peer observations and interactions rather than information disseminated by extension services such as agents from the local authority (Bakker et al., 2021; Krishnan and Patnam, 2014; Takahashi et al., 2019).

Next, we conducted a lab-in-field experiment in northern Vietnam. Following the definition of risk in previous studies (Bougherara et al., 2017), we quantify risk as the objective probabilities of all possible states of nature known to farmers, influencing their adoption decisions. Our experiment involves pairwise interactions between farmers, each deciding the proportion of their land allocated to conventional and organic agriculture. One farmer, designated as the leader, has all the information needed to adopt organic techniques and is the first mover in the group. We embrace the leader concept from social context studies (Garfield et al., 2020). Three scenarios are presented to farmers: (1) symmetric information, (2) asymmetric information favoring the leader, and (3) asymmetric information with the possibility of information sharing. Information sharing follows a Nash bargaining model (Nash, 1953), facilitating cooperation between farmers and sharing information.

Our experiment presents an interaction between two farmers deciding the proportion of their lands to conventional and organic agriculture. The two farmers face the same production function and the same risk. One of the farmers is a "leader": we define this farmer as the one who has equal or better information than the other farmer, and they always make decisions first. We adopt the leader's definition in studies about information sharing in the social context (Garfield et al., 2020). Farmers decide under three scenarios that we defined: (1) The two farmers get the same information, (2) The leader gets the better information, and (3) The leader gets better information, and the two farmers can share the information. The sharing information follows the Nash-Bargaining model (Nash, 1953). This model helps us to build a cooperation game between two farmers by providing the benefits of information sharing.

This paper proceeds as follows: Section 2 presents a theoretical model used in the experiment. Section 3 describes the experimental design. Section 5 presents the results and discusses them. Section 6 discusses and concludes the results.

4.2 Background and literature review

4.2.1 Organic agriculture in Vietnam

Vietnam is an agricultural country whose economy depends on the agricultural sector. This sector accounts for over 13 billion Vietnamese labor force and more than 40 percent of agricultural land (Dinh et al., 2023; Tran-Nam and Tiet, 2022). The development of farming production plays a vital role in the Vietnamese government's national food security and exportation strategy (Nguyen et al., 2022; Tran-Nam and Tiet, 2022). To improve farming productivity, Vietnamese farmers have used pesticides and chemical substances in their fields: the importation of pesticides in Vietnam has increased fivefold from 1990 to 2015. Although the farmers have attained high and stable yields to safeguard their income and the food security goal, the over-use of pesticides has caused alerting consequences such as farmer's health problems, chemical substances in farming products, soil degradation, water pollution, resistance of insects etc. (Berg and Tam, 2018; Dinh et al., 2023; Grovermann et al., 2024; Nguyen et al., 2022; Tran-Nam and Tiet, 2022; Vu et al., 2020).

Facing those problems, the Vietnamese government supports the development of sustainable agriculture such as crop rotation, conservation of soil and water practice, organic agriculture, etc, to mitigate the adverse effects of excessive use of pesticides and chemicals input and to secure the national food system (H.-G. Pham et al., 2021). Currently, organic agricultural land accounts for 1.1% of Vietnamese land and ranked thirty-second in terms of agricultural land among other countries (Dinh et al., 2023) and the Vietnamese government issued a decree for the development of organic agriculture until 2030: the organic agriculture land will obtain 3% of Vietnamese agricultural land Vietnamese Goverment, 2020. This goal strongly favors the conversion from conventional practice to organic practice in Vietnam. The transition requires farmers to decide to invest their land in organic agriculture.

However, the adoption level of organic agriculture among Vietnamese farmers is low (Boun My et al., 2022; Tran-Nam and Tiet, 2022). Firstly, the organic market in Vietnam is small and unstable to secure better economic benefits for farmers (N. H. My et al., 2017). Vietnam's government has not effectively implemented a certification system for organic food to build trust in consumer's choices of organic products (V. H. Pham et al., 2009). Then, the farmers have difficulties in the conversion, so their practices do not conform to the requirement for pesticides and fertilizers management (Toan et al., 2013).

The solution to farmer's adoption in Vietnam has attracted many studies. Some studies present that information obtained from the new practices improves farmers' preferences significantly(Vu et al., 2020). A lab-in-field experiment in northern Vietnam of Boun My et al. (2022) demonstrates the effects of social networks and social preferences on the uptake of organic farming in Vietnam. Factors such as training, certification, tracing system, neighbor's decisions and production cost, and leader's decision impact farmers' decision to stay in conventional practices or converse to organic practice (Tiet et al., 2021).

4.2.2 Adoption on organic agriculture

Economic factors in the adoption of organic agriculture strongly impact farmers' decisions. Changing to organic practices causes low yields and risk in final income from agriculture (Hermann et al., 2016). In a study of Kuminoff and Wossink (2010), U.S. farmers keep doing conventional agriculture because this practice compensates for higher profit than the profit in organic one. An increase in profit from organic adoption motivates conventional farmers to convert to this sustainable agriculture (Uematsu and Mishra, 2012).

Lack of information on organic practice and its corresponding unstable yield generate the risk on farmer's decision on conversation (Hermann et al., 2016; Läpple and Kelley, 2013)). For risk-aversion farmers, the effects of risk demotivate their investment in organic agriculture. The risk-neutral farmers invest at higher levels than more risk-aversion levels. Thus, monetary support from policymakers to raise the farmer's investment is necessary (Acs et al., 2009). Under the risk, risk-averse farmers tend to depend on pesticides to secure their productivity for a stable income (Mzoughi, 2011).

Seeking information is a prevalent practice among farmers. Uninformed farmers reach out to informed farmers about new practices so that they can adopt them or not (BenYishay and Mobarak, 2019). Furthermore, a reward to informed farmers for their information diffusion improved the proportion of new agricultural practices adopted in the village (BenYishay and Mobarak, 2019; Takahashi et al., 2019). Thus, the exchange of information plays a crucial role in the theoretical model developed in the next section.

4.3 Theoretical model

The theoretical model in this chapter is a simplified model developed in chapter 3 by focusing on the risk-neutral farmers and the equal Nash-bargaining power assumption for the lab-in-field experiment described in the following sections.

We are following the model in chapter 3, there are two farmers, denoted (l, f); each possesses one unit of agricultural land and decides allocation $x_i \in [0, 1]$, and $i = (l, f)$, land unit to organic agriculture; then, $1 - x_i$ is the land used for conventional agriculture. We assume that the land is a unique input in the production function of two practices.

Farmer l is a leader in the group. A leader is the first farmer to decide, and they constantly invest land to do organic agriculture such that $x_l > 0$. Follower f observes the leader's decision and then makes their own decision. The follower may or may not invest their land in organic agriculture such that $x_f \geq 0$.

We normalize the price of conventional products to 1. Then, the income from conventional agriculture is $b(1-x_i)-c(1-x_i)^2$. Let p be the price of the organic product. We assume a price premium for organic products such as $p > 1$. Thus, each allocation x_i, the income for organic products is $p\beta x_i - \alpha x_i^2 + s_i x_i$. Furthermore, doing organic farming allows farmers to receive a subsidy from the government of s_i per unit of allocated land. For any $x_i > 0$, the total income from organic investment is $\beta x_i - \alpha x_i^2 + s_i x_i = (\beta + s_i)x_i - \alpha x_i^2$.

The final income from a decision x_i is the sum of two types of farming and subsidy, such as:

$$\pi(x_i) = -(\alpha + c)x_i^2 + (p\beta + s_i - b + 2c)x_i + b - c \tag{4.1}$$

Let us consider the production risk be a known probability $\tau \in (0,1)$ that organic technology (α, β) equals (α_H, β_H), and $(1-\tau)$ if (α, β) equals (α_L, β_L): there are only two states of (α, β). All the parameters are positive. We further condition that $\pi(x_i; (\alpha_H, \beta_H) > \pi(x_i; (\alpha_L, \beta_L), \forall x_i \in [0,1]$; this leads to (1) if $\alpha_H \leq \alpha_L$, we must have $\beta_H \geq \beta_L$, (2) otherwise, $p(\beta_H - \beta_L) > \alpha_H - \alpha_L$. Farmers get positive income from conventional agriculture, or $\pi(x_i = 0) > 0$, thus $b > c$.

As in chapter 3, we put a condition on the leader's profit function such that $\pi(x_l; \beta_H, \alpha_H) > \pi(x_l; \beta_L, \alpha_L) > \pi(x_l = 0)$ so that leader constantly converses to organic agriculture. The subsidy needs to satisfy $s_l > b - 2c - p\beta_L$. However, we do not constrain the relationship follower's income with and without organic practice so that $\pi(x_f; \beta_i, \alpha_i) - \pi(x_f = 0)$ can take any sign.

4.3.1 The scenarios

Scenario 1: Complete and symmetric information

The leader and follower have all the information about their income function: they know whether they are in the High or Low organic state before the decision point. The farmer's problem in this scenario is to optimize their income by choosing x_i.

Let's consider the leader's decision, given that they receive the subsidy so that they always adopt organic agriculture. Their prediction decision then is such that

- If $(\alpha, \beta) = (\alpha_H, \beta_H)$:

$$x_l^{s_1} = \begin{cases} \frac{p\beta_H + s_l - b + 2c}{2(\alpha_H + c)}, & \text{if } \frac{b - 2c - s_i}{\beta_H} < p < \frac{b + 2\alpha_H - s_l}{\beta_H} \\ 1, & \text{if } p \geq \frac{b + 2\alpha_H - s_l}{\beta_H} \end{cases} \tag{4.2}$$

- If $(\alpha, \beta) = (\alpha_L, \beta_L)$:

$$x_l^{s_1} = \begin{cases} \frac{p\beta_L + s_l - b + 2c}{2(\alpha_L + c)}, & \text{if } \frac{b - 2c - s_f}{\beta_L} < p < \frac{b + 2\alpha_L - s_f}{\beta_L} \\ 1, & \text{if } p \geq \frac{b + 2\alpha_L - s_f}{\beta_L} \end{cases} \tag{4.3}$$

The follower also knows the actual state of organic agriculture from the results in Chapter 3. Their prediction decision then is such that

- If $(\alpha, \beta) = (\alpha_H, \beta_H)$:

$$x_f^{s_1} = \begin{cases} 0, & \text{if } p \leq \frac{b - 2c - s_f}{\beta_H} \\ \frac{p\beta_H + s_f - b + 2c}{2(\alpha_H + c)}, & \text{if } \frac{b - 2c - s_f}{\beta_H} < p < \frac{b + 2\alpha_H - s_f}{\beta_H} \\ 1, & \text{if } p \geq \frac{b + 2\alpha_H - s_f}{\beta_H} \end{cases} \tag{4.4}$$

- If $(\alpha, \beta) = (\alpha_L, \beta_L)$:

$$x_f^{s_1} = \begin{cases} 0, & \text{if } p \leq \frac{b - 2c - s_f}{\beta_L} \\ \frac{p\beta_L + s_f - b + 2c}{2(\alpha_L + c)}, & \text{if } \frac{b - 2c - s_f}{\beta_L} < p < \frac{b + 2\alpha_L - s_f}{\beta_L} \\ 1, & \text{if } p \geq \frac{b + 2\alpha_L - s_f}{\beta_L} \end{cases} \tag{4.5}$$

Scenario 2: Asymmetric information, no Nash-bargaining process

Only the leader knows the true state of organic technology at the decision point. The theoretical prediction states they will make the same decision as in scenario 1.

Otherwise, followers do not have such information, but they can still observe the leader's choice before making a decision. Given that the leader always does organic agriculture, followers cannot distinguish whether the income from adoption is better than staying with the conventional method. From this point, they decide under risk. We further assume that farmers are risk neutral and they have the expected utility of

Von Neumann and Morgenstern (2007); they choose to maximize the expected utility such that

$$x_f \in \underset{0 \leq x_f \leq 1}{\operatorname{argmax}} \, \tau\pi(x_f; \alpha_H, \beta_H) + (1-\tau)\pi(x_f; \alpha_L, \beta_L) \tag{4.6}$$

Solving the program in chapter 3, farmer's prediction decision such as

$$x_f^* = \frac{p[\tau\beta_H + (1-\tau)\beta_L] - b + 2c}{2([\tau\alpha_H + (1-\tau)\alpha_L] + c)} \tag{4.7}$$

Scenario 3: Asymmetric information, with Nash-bargaining process

Scenario 2 shows that a lack of information distorts the farmer's choice f; otherwise, they allocate the same amount of land as the farmer l. We call G_k, $k = (L, H)$, the income's differences of farmer f between the decision under full information and the one under risk, so $G_k = \pi(x_{f,k}; \alpha_k, \beta_k) - \pi(x_f^*)$ where $x_{f,k} = x_{l,k}$. We prove that $G_k = (\alpha_k + c)(x_{f,k} - x_f^*)^2 > 0$ (see Appendix for the prove). Knowing information benefits the farmer f in any state of organic technology: a rational farmer wants to obtain full information. In the model, the only mechanism of knowing the true state risk parameters is an informational transfer from farmer l to farmer f if such a process is available.

This scenario inherits all conditions from the previous one, but it lets two farmers join the information-sharing model defined next.

Our information-sharing model is a cooperation model since two agents increase their utility by cooperating. Without cooperation, two agents receive their utility as the disagreement points. These two principles approach our model to the Nash-bargaining model (Nash, 1953). Under Nash's axioms, the Nash-bargaining model finds a unique Pareto-efficient solution for a complete information game (Myerson, 1984). To satisfy the complete information condition, we further let agent f know the values of G_H and G_L, and agent l see the value of true G_k, given that l knows the actual state. Although f only knows the true gain after a negotiation finishes, they know precisely the gain received under both states at any decision point: they know all the necessary information about the final payoffs.

Consider that two farmers agree to negotiate on the information sharing. Let y_i be the percentage of G_k that farmer i proposes to maintain in the bargaining process. It is clearly that $y_l + y_k = 1$ and $s_i \in [0,1]$. In the bargaining, l negotiates the gain knowing given organic technology, thus their negotiating gain is $y_l G_k$. While f does not have this information, they bargain on the expected gain $\bar{G}s_f$ where $\bar{G} = \tau G_H + (1-\tau)G_L$.

The bargaining process starts with a proposition (y_l^1, y_f^1) from l to f. After receiving, f has two choices: (1) accept the proposition, then the bargaining ends; (2) reject the proposition, then they must propose another (y_l^2, y_f^2) to l. Farmer l has the same choices as f. A bargaining session then consists of a sequence of propositions and counter-propositions such as $\{(y_l^1, y_f^1), (y_l^2, y_f^2), \dots, (y_l^j, y_f^j), \dots\}$. We consider that there is a probability that the bargaining ends after the seventh round of proposition and counter-proposition. As in Nash's model, the constraint ensures that the strategy set is finite. However, the current model differs from the original one in allowing sequential bargaining. In Nash's bargaining case, two agents decide at the same time to have (s_l, s_f), and if this point is in an established feasible agreement set, then the agreement is set up. Otherwise, they receive a disagreement payoff. Rubinstein (1982) and Rubinstein (1985) prove that if the agents are risk-neutral, sequential bargaining models have a unique solution. Based on those results, our model has one Nash-equilibrium solution such that[1]

$$(y_l^*, y_f^*) \in \operatorname*{argmax}_{y_l + y_f = 1} y_l y_f \tag{4.8}$$

Solving the program, we have $y_l^* = y_f^* = 0.5$: two farmers share equally the gains.

[1] A more general model is asymmetric Nash-bargaining model which let the bargaining power parameter θ_i in the players such that $(y_l^*, y_f^*) \in \operatorname{argmax}_{y_l + y_f = 1} y_l^{\theta_l} y_f^{\theta_f}$ by Kalai (1977). In our model, two farmers are identical; they only differ from the information received. For the simplicity, we assume $\theta_l = \theta_f = 1$.

4.4 Experimental design

4.4.1 Treatments

In our experiment, we administer two treatments: (1) providing information on organic agriculture technology and (2) implementing a bargaining process. The control condition entails complete and symmetric information, where both farmers are aware of organic agriculture technology before making decisions, and no bargaining process is involved. We systematically examine these treatments alongside the control condition across three scenarios:

- Control: Both farmers possess complete and symmetric information about organic agriculture technology before making decisions, and there is no bargaining process.

- Asymmetric Information: Only farmer l possesses knowledge of organic agriculture technology before making decisions, and no bargaining process occurs.

- Asymmetric Information with Bargaining: Only farmer l possesses knowledge of organic agriculture technology before making decisions with a bargaining process for two farmers.

4.4.2 Experimental session

The experiment was implemented in North Vietnam in July 2022. We ran the experimental sessions in each village, at least two sessions per village. Each session consisted of four parts. At the beginning of a session, a member of the experimenters read the instructions about the experiment clearly, and instruction papers were also delivered to each farmer to read by themselves. The assistants supported the farmers in case of questions or difficulties on the iPad provided to all the players.

The first part measured the risk-averse level through a risk elicitation game as in Holt and Laury (2002). Farmers played a lottery game to choose between two options, A and B. Option A is a risk-free option in which farmers receive with certainty an amount of 50,000 VND (Vietnam Dong). Option B is a risk choice with a probability p to get a reward 100 000 VND and $1 - p$ chance to get 0 VND. There are a total of 10 risk choices with different probabilities. Farmers choose a switch point: all options above the switch point will be option A, and the ones under are option B. At the end of the session, the computer will run randomly to choose one of ten choices. There are two cases: (1) if that choice is option A, the farmer receives 50 000 VND; (2) if it is option B, the computer runs randomly, following the given probability of that choice, so that the farmer can get 100 000 VND or 0 VND. From this setting, the switching point helps to elicit the degree of risk aversion.

In the second part, we collected the data on social value orientation through a game developed in Murphy and Ackermann (2014) and Murphy et al. (2011). *Social value orientation* is intrinsic value of players in Nash-bargaining model (Luhan et al., 2019; Roth et al., 1981; Van Dijk et al., 2004). The differences in this value between players impact the bargaining power in the model, and then the Nash solution may deviate from the predictions. Thus, we measure this factor through part 2 to analyze Nash-bargaining results.

In this game, the computer randomly distributes six division tables to each farmer and assigns a group of two people. In each group, the farmer decides on each table respectively. In every table, there are ten choices to divide an amount of money between one's own and the other so that farmers choose the best division they desire. After making six choices, each farmer will randomly select a table. Then, the farmer will receive the money they devised for themselves and an amount their partner shared. We collect the choices in this part to measure the social value orientation.

The control and treatment were in the third part. Each farmer is assigned randomly to a group of two players. This group is the same in all the periods. Within a group, one farmer randomly is farmer l, called a leader. There are fifteen periods: five periods for the control scenarios, the following five for asymmetric information and without bargaining process treatment, and the last five for asymmetric information and bargaining process treatment. During the fifteen periods, the two farmers in a group have the same organic technology to have the same payoff function. The leader decides first x_l; then, the farmer f receives the value of x_l, and then they allocate x_f. When all players choose, they receive information about their earnings in that period. Depending on the treatments, modifications in the payoff function will be introduced to the farmer f. We use the *within-subject* design because this provides a higher number of observation points and then improves the statistical analysis, given our small sample size (Charness et al., 2012).

In the first five periods, farmers allocate x_i percent of the land they adopt to organic agriculture and keep $1 - x$ percent of the land for conventional agriculture. The payoffs of farmers will change in each period because they depend on the organic technology in that specific period. We give them two payoff functions as follows:

- Under the High organic agriculture:

$$P_i = 75000 + 160500x_i - 100000x_i^2 \tag{4.9}$$

- Under the Low organic agriculture:

$$P_i = 75000 + 45000x_i - 115000x_i^2 \tag{4.10}$$

Earning ranges from 75 000 VND ($x_i = 0$) to 139 400 VND (at optimal level $x_i = 0.8$) if technology is at high, or to 79 400 VND (at optimal level $x_i = 0.2$ if technology is at Low). On the game's screen, players can see the payoffs of their decisions by moving a slider. They do not calculate the formula by themselves so that we can avoid the cognitive burdens in farmers' decisions.

Leaders will still receive the complete information in the successive five periods, while followers will not receive the information on organic technology. We let farmer f make two choices: one for the allocation as if the technology is at high, and the other for the allocation as if the technology happens at Low. Recall that they decide after knowing x_l. Thus, there are two allocations: x_f^L for Low and x_f^H for high. At the end of each period, they realize the organic technology and an earning corresponding to x_f^L or x_f^H.

Farmers start by deciding in the last five periods, as in Scenario 2. A table that provides the potential G_k to the leader and potential gains G_L and G_H to farmers f, and two farmers have to decide whether they want to join a bargaining process to share those gains. If both farmers agree, they will start bargaining part; otherwise, the period ends, and they receive payoffs from their previous allocation.

At the end, the computer randomly chooses a period to calculate the farmer's payoffs in Part 3. The total payoffs of a farmer are the sum of earnings from Part 1, Part 2, and Part 3. The maximized payoffs in each part are not greatly different from each other to avoid the *hedging behavior* so that farmers keep the incentive to achieve the highest payoffs in each part. (see the Supporting section 4.8.1 for the introduction of the experiment).

At the beginning of the new treatment, farmers answer a set of *understanding questions* to evaluate their knowledge of the upcoming periods. If there are wrong answers, an assistant will explain the answer again so that farmers understand clearly before playing.

Finally, farmers are requested to answer a questionnaire. Through that, we collect further information about the environmental concerns (Schultz, 2001), the age, gender, education level, farm characteristics, income, health, risk attitudes, etc.

4.4.3 Theoretical predictions

Under the experimental design and the theoretical model, we predict that in Scenario 1:

Theoretical prediction 4.4.1. *All farmers invest 80% of their land in organic agriculture if the organic state is High. If the organic state is low, they invest 20%.*

In Scenario 2:

Theoretical prediction 4.4.2. *Leaders' decisions are the same as in Scenario 1*

In Scenario 3, the bargaining follows the Nash-Bargaining model as in equation (4.8); we then have predictions:

Theoretical prediction 4.4.3. *All farmers agree to bargain a sharing gain from the information obtained*

Theoretical prediction 4.4.4. *Farmers agree on equal gains (50%) from information shared after the bargaining*

4.5 Sample

4.5.1 Descriptive statistics for the whole sample

The sample consists of 186 farmers from Northern Vietnam. There are eleven sessions in five villages: Dan Nhiem (two sessions with 32 farmers), Hien Giang (two sessions with 38 farmers), Hong Ha (three sessions with 46 farmers), Song Phuong (two sessions with 28 farmers), and Tien Duong (two sessions with 42 farmers).

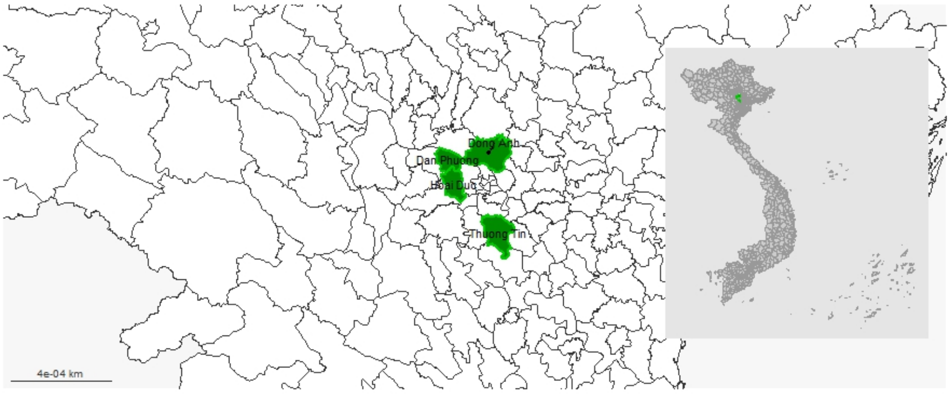


Figure 4.1: Map of villages in the experiment

Each session consists of three experimental parts: the risk elicitation, the social value orientation elicitation, and the third part on the land allocation decision. In the third part, farmers were assigned to groups of two members. Thus, 93 groups were assigned to play through three scenarios in 15 periods for this part. We collected 2790 decisions on organic agriculture adoption, including 465 decisions for the treatment with the bargaining process.

Table 4.1 presents the characteristics of farmers. The average age is about 54 years old; the youngest is 19 years old, and the oldest is 80 years old. Agriculture activities are the primary income of more than 72.6 percent of farmers. The average land size is 1,340 square meters, and the largest land size is 20,000 square meters. The crops cultivated are rice (53.36%), vegetables (35.75%), fruits (32.96%), and other styles; notice that 62 farmers (33.33%) planned more than two styles of crops in their lands.

Table 4.1: Descriptive characteristics of farmers

	N	Mean	St. Dev.	Min	Max
Age	186	54.145	12.603	19	80
Gender	186	1.709	0.455	1	2
Egoist (Environment concern)	186	6.630	0.736	3.75	7
Biosphere (Environment concern)	186	6.369	1.036	1	7
Altruist (Environment concern)	186	6.622	0.838	2.250	7
Household income	186	3.073	1.622	1	6
Income from farming	186	0.726	0.447	0	1
Land size (in 1000 m^2)	186	1.34	2.097	0	20
Rice	186	0.536	0.5	0	1
Vegetable	186	0.358	0.481	0	1
Fruit	186	0.33	0.471	0	1
Corn	186	0.084	0.278	0	1
Other	186	0.128	0.336	0	1
Information on organic	186	1.324	0.469	1	2
Organic agriculture is difficult	186	0.344	0.478	0	1
In Organic product demand	186	0.16	0.368	0	1
Other difficulties	186	0.617	0.489	0	1

None of the farmers follow entirely the regulations on organic agriculture to get an official certification. Only 32.4 % confirmed that they had heard about this notion but had not practiced it yet. Among the reasons why they have not followed the organic methods, 34.41 % believed that doing organic agriculture is difficult; 15.78 % said that they worry about the demand side of organic products; 61 % responded to other difficulties.

Following the guideline from Murphy et al. (2011), the *Social value orientation* scores are measured to categorize farmers. The results in Table indicate that 62.9 % of farmers are in *Altruist* oriented group, 23.1% are in *Prosocial* oriented group, while the Individualist orientation and Competitive orientation account for 9.68% and 4.3% respectively.

Table 4.2: Distribution of Social value orientation variable

Category	Number of farmers	Proportion (in percentage)
Altruist orientation	117	62.9%
Pro-social orientation	43	23.1%
Individual orientation	18	9.68%
Competitive orientation	8	4.3%

4.5.2 Descriptive statistics for leader and follower groups

In this section, we observe leaders' and followers' characteristics. As illustrated in Table 4.3, the average age of leaders is 55.48, and followers are 52.98. 75.3 % of leaders are women, and it is 66.3 % of followers. The average income level is similar, from 10 million VND to 20 million VND. Crop diversification happens in both groups with similar patterns.

Concerning the SVO, the more than 60% farmers in two groups are in *Altruist*, and 20% are in *Prosocial*. Thus, the leaders and followers are assigned randomly and keep the presentation characteristics of the whole sample. The similarity of personal attributes in the two groups helps us focus on the differences in treatment and information provided in adoption decisions that we analyze in the following sections.

Table 4.3: Descriptive characteristics of leaders and followers

Statistic		Leader				Follower			
	N	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
age	93	55.484	11.743	19	80	52.698	13.389	20	77
gender	93	1.753	0.434	1	2	1.663	0.476	1	2
Egoist	93	6.688	0.698	3.75	7	6.567	0.775	3.750	7
Biosphere	93	6.384	1.091	1	7	6.352	0.980	3.500	7
household income	93	3.086	1.62	1	6	3.058	1.633	1	6
income from farming	93	0.677	0.47	0	1	0.779	0.417	0	1
land size (in 1000 m^2)	93	1.328	2.141	0	20	1.352	2.061	0	15
rice	93	0.559	0.499	0	1	0.512	0.503	0	1
vegetable	93	0.344	0.478	0	1	0.372	0.486	0	1
fruit	93	0.333	0.474	0	1	0.326	0.471	0	1
corn	93	0.086	0.282	0	1	0.081	0.275	0	1
other	93	0.097	0.297	0	1	0.163	0.371	0	1
information on organic	93	1.376	0.487	1	2	1.267	0.445	1	2
doing organic	93	1.591	0.494	1	2	1.442	0.500	1	2
organic difficult	55	0.4	0.494	0	1	0.263	0.446	0	1
organic product demand	55	0.145	0.356	0	1	0.179	0.389	0	1
other difficulties	55	0.582	0.498	0	1	0.667	0.478	0	1

4.6 Results and discussions

4.6.1 Theoretical predictions for Scenarios 1 and 2

In this section, we analyze the average decisions of leaders and followers in scenarios 1 and 2 to test our predictions.

Under the first scenario, two farmers receive the same information, and leaders allocated, on average, 66.7% if high organic technology happens and 38.9% if low organic technology happens. Followers decide 69.8% for high organic technology and 42.8% for low organic technology. Thus, we observe a slightly higher allocation in followers than in leaders. We use the Wilcoxon signed rank test, a non-parametric estimator, to verify the statistically significant difference in mean between the two groups. The theoretical model predicted that leaders and followers, given complete information, invest 80% of their lands under high organic technology and 20% under low organic technology. The Wilcoxon signed rank test supports the Prediction 4.4.1; the p-value is at 0.2662.

If only leaders knew the organic technology and without a bargaining process, leaders would have the same information as in scenario 1, with leaders 66.1% to organic agriculture under high organic technology and 33.1% under low organic technology. Prediction 4.4.2 expects that the decisions are to be the same. The Wilcoxon signed rank test between leaders' decisions under two Scenarios accepts, at 5 % significant level; thus, the data supports the Prediction 4.4.2.

Besides, in Scenario 2, followers invested, on average, 37% of land in low states and 65.8% of land in high states. The adoption levels are lower than those in Scenario 1. These changes could be the effect of risk in Scenario 2. Although farmers can decide in two situations, they are not given the actual value of organic agriculture. Thus, they could feel the risk of incomplete information.

4.6.2 Theoretical prediction for Scenario 3

Prediction 4.4.3: All farmers agree to bargain a sharing gain from the information obtained

In this scenario, two farmers in a group can join a bargaining process. The process is a mechanism that helps followers realize the potential gains and bargain partly with leaders. Before coming to the bargaining decision, farmers decide as if they are in Scenario 2, leaders allocates on average 67.3% lands to organic agriculture if its technology happens at high, otherwise they invest 32.4%.

The Wilcoxon signed rank test on the leader's decision in this scenario, and the second scenario fails to reject that the difference in the mean is zero. Thus, the leader's decisions under the two scenarios are the same. The average allocation of followers at high is 67.6%, and at low is 33.7%. The Wilcoxon signed rank tests show that there are statistical differences between followers' decisions in scenarios 2 and 3.

Table 4.4: Agreement to participate in bargaining step

Periods	**Agree to bargaining (in %)**
11	79.6
12	86.0
13	81.7
14	86.0
15	87.1
Total	**84.1**

We observe that followers could increase their payoffs by choosing the optimal adoption level. The gains G_k are positive in all of the experiments: on average, gains under high organic technology are at 15 428 VND, and under low organic technology are at 13 609 VND. There are incentives to join the bargaining step. In the experiment, there are 84.1% farmers group agree to bargain, the percentage to join is lowest at the eleventh period (79.6%) and highest at the fifteenth period (87.1%) as shown in Table 4.4. These high percentages prove the substantial predictive property of our bargaining model.

Prediction 4.4.4: Farmers agree on equal gains (50%) after the bargaining

Furthermore, 97.03% of the bargaining groups agree to share gains between leader and follower. As shown in Figure 4.2, the only modal point of the share is at 0.5, supporting the Prediction 4.4.4. We use the Wilcoxon signed test between theoretical prediction and the empirical shares. The result shows that $p - value = 0.8809$: there is no difference in mean between theoretical model prediction and the shares agreed between farmers. The data supported the Prediction 4.4.4 strongly.

The experiment contains 391 bargaining periods. 186 negotiation ends with the share 0.5, so about 47.5% of successful agreement. It seems that more than 50% of the agreement does not conform to Prediction 4.4.4. We observed further in Figure 4.2 a

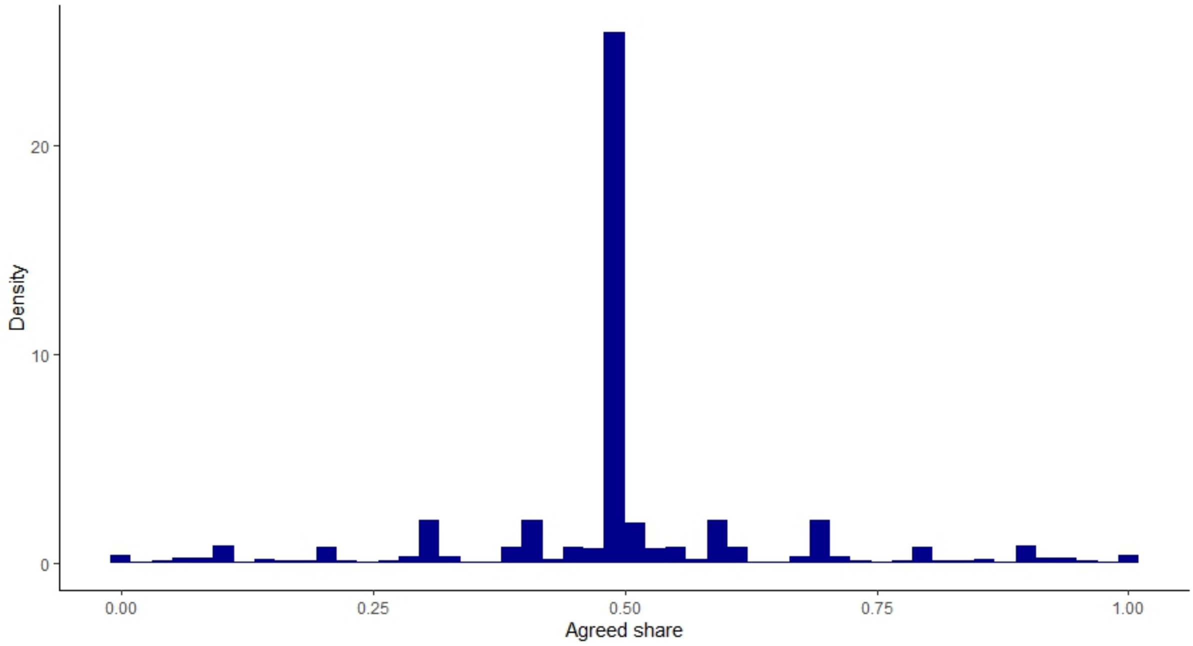


Figure 4.2: Histogram on the bargaining share

spread in the share around the theoretical point; thus, we will analyze the factors that influenced the leader and farmer decisions.

Our theoretical model assumes that leader and follower are equal in bargaining power. This assumption cannot explain why 52.5% agreements differ from the equal share predicted above. Other factors could impact the farmers' decisions in the bargaining process. Firstly, the risk aversion of a player alters the bargaining power (Luhan et al., 2019; Roth and Rothblum, 1982). In our experiment, the bargaining process ends (with 50% in probability) after the seventh round of propositions and counter-propositions. Thus, the farmers face a risk of ending up without any agreement. The higher risk-aversion farmers are, the less bargaining power they have, as proved in the study of Roth and Rothblum (1982).

Secondly, sociology factors such as social value orientations are intrinsic factors that can alter the prediction of the Nash-Bargaining model (Roth et al., 1981). Van Dijk et al. (2004) experimented to examine the role of social value orientation on the Nash-bargaining game. The authors found that those values motivate the farmers to pursue and accept the propositions related to their social values.

In the next section, we analyze the effects of the above factors on the bargaining share in our experiment. The risk level and social value orientation are the main explanatory variables in the econometric model developed below.

Econometric model on bargaining share

In this section, we develop the econometric models to analyze the farmers' decisions on the allocation to organic agriculture and their decisions on the share in bargaining. Each farmer plays the bargaining game five times (from period 11 to period 15). Thus, our sample's data is panel data with relatively few periods. Let s_{it} be the agreed share of farmer i in period t, and their time-variance explanatory variables represent by vector $\mathbf{x_{it}}$, and time-constant variables represent by vector $\mathbf{z_i}$ and individual unobserved effects c_i, we have the regression model such that

$$s_{it} = E[s_{it}|\mathbf{x}_{it}, \mathbf{z_i}, c_i] + \epsilon_{it} \tag{4.11}$$

Under standard linear assumption, $E[s_{it}|\mathbf{x}_{it}, \mathbf{z_i}, c_i] = \mathbf{x}_{it}\boldsymbol{\beta_1} + \mathbf{z_i}\boldsymbol{\beta_2} + c_i$, then regression is rewritten as $s_{it} = \mathbf{x}_{it}\boldsymbol{\beta_1} + \mathbf{z_i}\boldsymbol{\beta_2} + c_i + \epsilon_{it}$. However, s_{it} is in $[0, 1]$, and the linear model could not explain well the non-linear relationships; we then apply the fractional response variables model developed in Papke and Wooldridge (1996, 2008) and adopted in a lab-in-field experiment on the Vietnamese farmers' adoption to organic agriculture in the study of K. B. My et al. (2022). We consider that

$$E(s_{it}|\boldsymbol{x}_{it}, \mathbf{z_i}, c_i) = \mathrm{G}(\mathbf{x}_{it}\boldsymbol{\beta_1} + \mathbf{z_i}\boldsymbol{\beta_2} + c_i) \tag{4.12}$$

G(.) is a nonlinear function with its values in $[0, 1]$. The logistic function form $\frac{e^{\mathbf{x}_{it}\boldsymbol{\beta_1}+\mathbf{z_i}\boldsymbol{\beta_2}}}{1+e^{\mathbf{x}_{it}\boldsymbol{\beta_1}+\mathbf{z_i}\boldsymbol{\beta_2}}}$ and probit function form $\Phi(\mathrm{G}(\mathbf{x}_{it}\boldsymbol{\beta_1} + \mathbf{z_i}\boldsymbol{\beta_2}))$ are two good choices for G(.). If the dependent variable is a binary choice, there are not many differences between the logit and probit functions, but probit functions guarantee better consistent properties in estimating for the panel data models (Papke and Wooldridge, 2008). We then adopt the function form Papke and Wooldridge (2008) such that

$$E(s_{it}|x_{it}, \mathbf{z_i}) \equiv \Phi(x_{it}\beta_1 + \mathbf{z_i}\boldsymbol{\beta_2} + \bar{x}_i\xi) \tag{4.13}$$

Where x_{it} is *total potential gain* negotiate from information in the bargaining process between leader i in period t and their follower; $\bar{x}_i$ present average of potential gain over five periods such that $\bar{x}_i = \sum_{t=1}^{5} x_{it}$. The set of time-constant explanatory variables in $\boldsymbol{z_i}$ include *Biophere*, *Egoist*, *Altruist*, *Social value orientation*, *Attitude toward risk*; other control variables are *Gender*, *Age*, *Education*, and *Household's income*.

We use the pooled Quasi Maximum Log-Likelihood for the Bernoulli function in regression function $\Phi(x_{it}\beta_1 + \mathbf{z_i}\boldsymbol{\beta_2} + \bar{x}_i\xi)$ (Papke and Wooldridge, 1996, 2008; Ramalho, 2019). The estimator is not an optimal solution if many observations are at boundaries $s_i = 0$ or $s_i = 1$ (Ramalho, 2019). In our sample, only four shares at boundary ($s_l = 1, s_f = 0$) account for only 0.5%; thus, the fractional response variables model is a good choice for our analysis.

Bargaining share and its explanatory variables

Our dependent variable is the agreed share in a bargaining step, from 0% to 100%. Its mean is 0.5. We use a set of interested variables as explanatory variables: total gain to negotiate from bargaining, environmental concern, and social value orientation; socio-demographic variables are the control variables. Table 4.5 presents the descriptive values of those variables.

Social value orientation, *Altruist* farmers account for around 62.9% in our sample; the second largest group is *Pro-social* value, with 23.1%. The other two groups (*Individual value* and *Competitive value*) share small proportions in our sample.

Gain in high and *Gain in low* measure the potential gain in thousand VND that two farmers bargain to share. These values are presented to farmers during the negotiation. Environmental concerns are twelve questions in linkert-scales from 0 (do not concern at all) to 1 (totally concern).

The set of socio-economic variables include *gender*, which takes value 1 if they are women, and 2 if they are men; *(*age);*education* with seven levels; *household income* measures the total income in a household with four income ranges (below 6 million VND, from 6 to 10 million VND, from 10 to below 20 million VND, and from 20 million VND).

Table 4.5: Descriptive statistic of dependent variable and explanatory variables

Statistic	N	Mean	St. Dev.	Min	Max
Dependent variable					
Share	776	0.5	0.163	0	1
Explanatory variable:					
Risk attitude	742	6.24	3.55	1	10
Control variables:					
Gain in high	776	15,428.25	9,593.475	10,000	59,350
Gain in low	776	13,609.53	10,461.43	8,000	81,600
Gender	742	1.703	0.457	1	2
Age	742	54.467	12.491	19	80
Education	742	3.643	1.409	1	7
Household's income	742	3.116	1.618	1	6

Note: 186 leaders and followers were asked to join bargaining during five periods. Thus, 930 decisions were made: 776 decisions to join the bargaining (accounting for 83.4%) and 154 decisions not to join the bargaining (accounting for 12.6%). We then analyzed the agreed share from 776 observations. 34 observations of independent variables from six followers were missed. Thus, there are 742 observations for the *Risk attitude* and other control variables.

Econometric results on leader's agreed share

Table 4.6 presents the analysis of the leader's decision on bargaining share. The leaders with *competitive* social value orientation show higher bargaining share than *altruistic* leaders. It seems that altruistic leaders weigh the benefit of followers in their negotiations and show less demand than other types of leaders. The *individual social orientation* and *pro-social social orientation* do not significantly affect the leader's decision to share with followers.

Table 4.6: Regression results on leader's decision in bargaining share

	Dependent variable: Leader's share y_l		
	Linear pool effect	Linear random effect	Fractional model
	(1)	(2)	(3)
SVO:Competitive	0.094^{**}	0.108^{**}	0.242^{**}
	(0.042)	(0.044)	(0.119)
SVO:Individual	0.045	0.030	0.115
	(0.031)	(0.024)	(0.086)
SVO:Pro-social	−0.002	−0.008	0.0002
	(0.021)	(0.020)	(0.053)
Risk Attitude	−0.004	−0.004	−0.010
	(0.004)	(0.003)	(0.012)
Constant	0.201	0.240	−1.060
	(0.180)	(0.191)	(0.665)
Control variables included	Yes	Yes	Yes
Observations	388	388	388

Note: The dependent variable is the leader's share in the bargaining game. Bootstrapp-clustered standard errors in the parentheses. The compared factor for SVO is SVO:Altruist. Control variables are Age, Education, Gain to bargain, Gender, Household income, and Organic at Low. *p<0.1; **p<0.05; ***p<0.01

We can also see that the data does not support the role of the *Risk attitude* in the bargaining results. Leaders and followers do not consider the risk in the negotiation. One possible explanation comes from the number of propositions observed in the data. 93% of the negotiations ended after the first round of propositions (including one proposition from the leader and a counter-proposition from the follower). These do not have any negotiation that lasted over 5 rounds of propositions. Thus, the risk of suddenly ending the negotiation after 7 rounds does not impact the farmer's bargaining decision in our experiment.

Table 4.7 shows regression results on the leader's agreed share under the low and high organic states. The results are consistent with the estimates under the whole sample. Leaders with a *competitive* value orientation tend to be more demanding in the negotiation. Murphy et al. (2011) defines this value as a desire to maximize the differences between self and others. This supports a positive relationship between *competitive* orientation and share demand. These results are generally consistent with an experiment in Roth et al. (1981). The authors also found that non-strategic factors such as norms and personal values significantly systematically impact the bargaining results between two players.

Table 4.7: Leader's decision on share: Sample at High and Low organic state

	Dependent variable: Leader's agreed share					
	High organic technology			Low organic technology		
	Linear panel function		*Fractional function*	*Linear panel function*		*Fractional function*
	Pool	Random effect	Fractional Probit	Pool	Random effect	Fractional Probit
	(1)	(2)	(3)	(4)	(5)	(6)
SVO:Competitive	0.082^{**}	0.082^{**}	0.207^{***}	0.102^{*}	0.115	0.256^{*}
	(0.039)	(0.041)	(0.077)	(0.060)	(0.076)	(0.141)
SVO:Individual	0.075	0.054	0.189	0.012	0.012	0.031
	(0.065)	(0.062)	(0.116)	(0.060)	(0.061)	(0.122)
SVO:Prosocial	0.008	−0.002	0.021	−0.008	−0.006	−0.020
	(0.033)	(0.033)	(0.068)	(0.028)	(0.030)	(0.074)
Risk attidude	−0.004	−0.003	−0.009	−0.003	−0.003	−0.008
	(0.009)	(0.008)	(0.017)	(0.007)	(0.007)	(0.016)
Constant	0.231	0.212	−0.679	0.160	0.228	−0.855
	(0.320)	(0.241)	(0.624)	(0.261)	(0.262)	(0.630)
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes
Observations	198	198	198	190	190	190

Note: The dependent variable is the leader's share in the bargaining game. Robust-clustered standard errors in the parentheses. The compared factor for SVO is SVO:Altruist. Control variables are Age, Education, Gain to bargain, Gender, Household income, and Organic at Low. *p<0.1; **p<0.05; ***p<0.01

Econometric results on follower's agreed share

This section analyzes the follower's decision on the bargaining share. The difference between bargaining with the leader and the follower is that the follower does not know the true potential gain; thus, we take the average of high gain and low gain in the regression.

Table 4.8: Follower's decision on share

	Dependent variable: Follower's share		
	Linear pool effect	Linear random effect	Fractional model
	(1)	(2)	(3)
SVO:Competitive	0.012	0.013	0.029
	(0.036)	(0.035)	(0.091)
SVO:Individual	−0.012	−0.014	−0.031
	(0.031)	(0.028)	(0.073)
SVO:Prosocial	-0.044^{**}	-0.049^{***}	-0.112^{**}
	(0.022)	(0.016)	(0.054)
Risk Attitude	−0.005	−0.006	−0.012
	(0.005)	(0.004)	(0.012)
Constant	0.716^{***}	0.579^{**}	0.543
	(0.234)	(0.232)	(0.604)
Control variables included	Yes	Yes	Yes
Observations	354	354	354

Note: The dependent variable is the follower's share in a bargaining game. Robust bootstrap-clustered standard errors in the parentheses. The compared factor for SVO is SVO:Altruist. Control variables are Age, Education, Average gain, Gender, Household income, and Organic at Low. *p<0.1; **p<0.05; ***p<0.01

In Table 4.8, followers' decisions are influenced by the *prosocial value orientation* value. This value is supported in all three models with very high significant levels. This value presents the motivation to achieve the highest social value in bargaining (Murphy and Ackermann, 2014; Murphy et al., 2011). From the Nash-bargaining solution, this value orientation emphasizes an equal gain between leaders and farmers. The negative effect could be explained by the *altruist value orientation*, a base level, motivating the followers to give leaders a higher share than the *prosocial value orientation* does. Furthermore, the role of *prosocial value orientation* could be from the fear of *reject* from other because the fairness impacts on the choice of proposition (Luhan et al., 2019; Roth et al., 1981). Farmers could form subjective beliefs that the leader may accept fairness share, and thus they try to play as an *prosocial value orientation* player as their strategy (Van Dijk et al., 2004).

The *risk attitude* does not influence followers' decisions. These results strengthen the conclusion that the risk is not a significant factor explaining the farmer's decision because most farmers concluded their bargaining in the first round (Nash, 1953; Rubinstein, 1982, 1985).

The results lead to one noticeable point: social value orientations impact leaders and followers differently. While *competitive value orientation* is a significant factor in a leader's decision, follower's results do not support this. Similarly, *prosocial value orientation* motivates the follower, while we cannot prove this in the leader's decision. In our experiment, leaders know the actual gain they are bargaining for, while followers do not have this information. In the view of leaders, they bargain to achieve the highest monetary payoffs, and for followers, they bargain on the proportion of unknown gain. This is *partial information* bargaining game defined in Roth and Murnighan (1982). In this game, a subject who has full information maximizes their payoffs and deviates from equal share, while the subject whose information is partial tends to equal share, as our results indicate.

4.7 Conclusion

Our theoretical model focuses on the cooperation between farmers to get adequate information to overcome constraints in organic agriculture adoption. The first theoretical prediction is that all farmers agree to bargain on the information-sharing benefits. The results in the study support this prediction, with more than 80% farmers bargaining in scenario 3. Information seeking is in high demand from farmers when they face the risk of agricultural activities. The model fits the empirical studies such that farmers are likelier to seek information from other farmers in their communities (Bakker et al., 2021). Furthermore, informed farmers are a key factor in diffusing information and impacting the decision of new practices such as organic agriculture (Takahashi et al., 2019). Those results recommend an approach to information diffusion policy to promote organic agriculture rather than traditional methods such as service extensions.

Secondly, empirical studies suggest using monetary rewards to facilitate information diffusion. Without such incentives, leaders are unwilling to share advantaged information with other farmers. Thus, we adopt the Nash-bargaining model in information diffusion and observe the conformity between theoretical predictions and empirical share. Therefore, the results highly support that equal gains at 50% for both farmers are focal points in the bargaining step, as predicted in our model. We also observe that more than 50% farmers agree on the share other than equal gains; we verify the factors that could impact the decisions observed. The competitiveness of leaders increases their demand in the bargaining game significantly. Interestingly, the study suggests the role of *Prosocial* on the bargaining model; the benefit of the group to achieve an agreement is valuable to players so that they can lower the proposition to avoid the risk of disagreement. Overall, non-monetary factors such as social value orientation significantly impact Nash's model (Roth et al., 1981). Those findings pave the way for a demand to extend our model to capture the non-monetary incentives in cooperation and information sharing.

The results do not support the idea that risk attitude impacts farmer decisions. The reason may be that farmers choose their best proposition as the early round of propositions, so they will not reach the seventh round to face a risk.

We also observe a reduction in the allocation of followers to organic agriculture when they lack information in scenarios 2 and 3 compared to scenario 1. A risk in production function constrains the adoption of organic agriculture as seen in many empirical studies (BenYishay and Mobarak, 2019; Bontemps et al., 2021; Bougherara et al., 2017). Thus, the results justify a model that helps farmers overcome the risk by obtaining complete information.

Further development

Firstly, the theoretical model assumes equal bargaining powers between leader and followers. In chapter 3, the model's solution presents the final shares depending on relative bargaining power between two farmers. The asymmetric Nash-bargaining model could be further developed for the lab-in-field experiment to capture the differences in the bargaining powers of farmers.

Secondly, our sample consists of 186 farmers in Northern Vietnam; it does not represent data in Vietnam. Measuring the farmers' behavior in other regions of Vietnam is essential to construct a comprehensive analysis of the role of information sharing and generalize the results for the external validity value.

The *within-subject design* has its advantages in our experiment. However, this design may have the *experimenter-effect* and *context-effect*. A design that combines *between-subject* and *within-subject* design could improve the results (Charness et al., 2012). Besides, the *survey fatigue* may exist in some farmers, and the experimenter could not control this problem. If the number of subjects can increase, we can reduce the periods in Part 3 of the experiment, but the total observations (numbers of subjects multiplied by the periods) are not reduced to avoid the *survey fatigue*.

Finally, as shown in the results, our models must extend the non-monetary factors on the adoption and bargaining solution. The model assumes risk-neutral farmers, and then the experiment is constructed such that followers can decide, with certainty, that they have two choices for two states of organic agriculture. However, the results show the effect of risk in scenario 1 and scenario 2. A model that predicts a farmer's risk attitude and decision is a further approach for a new experiment.

4.8 Supplementary information

4.8.1 Experiment introduction to farmers

Good day and welcome all of you.

We would like to thank you for participating in this economic experiment.

You are going to participate in an experiment in which you will make your own decisions for each of the parts of the experiment. You do not need to have any prior or specific knowledge to attend this experiment. And, there is no right or wrong answer for your decisions. We only require that your decisions sincerely reflect your choices.

All your decisions in this experiment are anonymous. We do not record your name during the experiment.

During the experiment, you will not be allowed to communicate verbally with other participants if the Part does not allow, or use any electronic devices such as telephone.

If you have any questions, please raise your hand and one of our assistants will approach you.

Your gains from this experiment depends on your decisions. In the particular Part, your gains can depend partly on the decisions of other participants who you will play with and partly on the random process (computer, cards, coins…).

This experiment will have three parts. You will receive a new introduction before starting a new part. In each part, you will make your decisions following the introduction and the tasks.

You will get the gains from each part. Your total gains are the sum of the gains from each part. The total gain will be given to you in cash at the end of the experiment privately to ensure that only you know your gains. After finishing three parts, you will answer to a questionnaire. This questionnaire helps us to understand you better. You will not lose any money in this experiment.

Before we start the first part, if you have any question, please raise your hand. Our assistant will come to you.

Part 1

Before starting this part, you will choose your winning color, yellow or blue.

In this Part, you will make a series of decisions in choosing between two options: - The Left option is a risk option - The Right option is riskless.

The Left option involves randomly picking a ball from an urn containing 5 yellow and 5 blue balls. If the ball's color is the same as your winning color, you win 100,000 VND. If the ball's color is not the same as your winning color, you win 0 VND.

The Right option gives you a certain amount of X VND, which varies from 0 VND to 100 000 VND

Notices:

If you prefer the Left Option to an amount of X VND, it will be the same for all amounts less than X VND. If you prefer the Right Option to an amount of X VND, then it will be the same for all amounts greater than X VND.

Your gains:

Firstly, the computer randomly chooses a line in the table to decide the amount X. Then,

If you choose the Left Option for this line, a ball will be randomly picked up in the urn and if the ball's color is the same as your winning color, you will win 100 000 VND, if not you will win 0 VND

If you choose the Right Option for this line, you will get the X VND.

Example:

If you want to choose the Left option for all the amount X is less than 50 000 VND and the Right option for all the amount X from 50 000 VND, you choose the Right option at line X = 50 000 VND. The computer will automatically choose the Left option for all the X less than 50 000 VND and the Right option for all lines with X from 50 000 VND.

There is no right or wrong decision. We only want you to choose the option that you prefer the most.

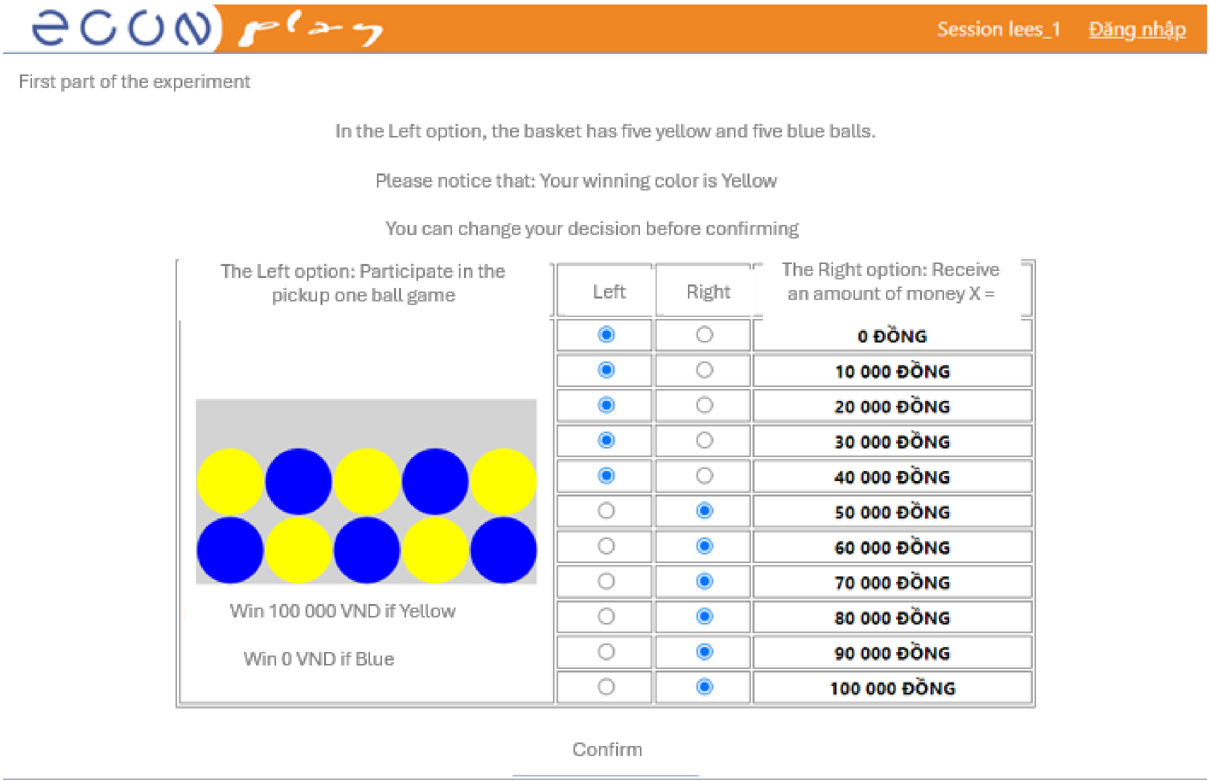


Figure 4.3: Example of risk elicitation game

Part 2

This Part is independent of the previous Part.

In this Part, you will decide on a distribution of money between you and other people.

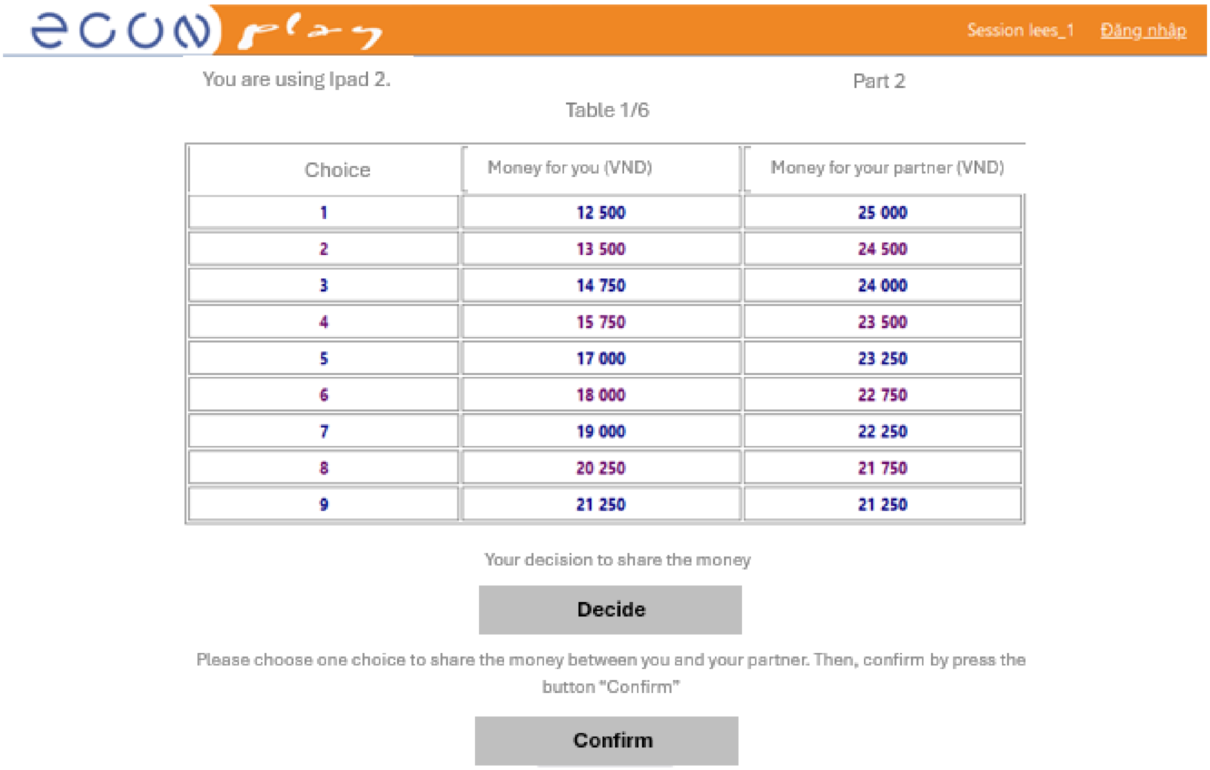
This money does not relate to the money you gained from the previous Part or your own money. You will earn more money from this part depending on your decision.

Your decision:

You make six decisions. Each time, there is a table describing the 9 distribution of money between you and the other. You choose one and only one distribution that you prefer the most. There is no right and wrong allocation from your choice. Thus, please choose the allocation that you prefer most.

There is an example below:

As you can see in the example, there are three columns on the table. The first column



Choice	Money for you (VND)	Money for your partner (VND)
1	12 500	25 000
2	13 500	24 500
3	14 750	24 000
4	15 750	23 500
5	17 000	23 250
6	18 000	22 750
7	19 000	22 250
8	20 250	21 750
9	21 250	21 250

Figure 4.4: Example of SVO game

is the distribution number; the second column is the money that you get for yourself; and the third column is the money that you decide for the other. You will choose between 9 given distributions.

Your gain:

At the end of the gain, you are randomly assigned to another player in the session. You do not know who your partner is, and neither does your partner. Then, a table will be randomly chosen from 6 tables.

Your gain is the sum of the money that you decide for yourself in that table and of the money given by your partner's decision. For example, if the table above is randomly chosen. In that table, you decided on distribution 5, and your partner decided on distribution 6. Then, your gain is the sum of 17 000 from your decision and 22 750 from your partner's decision, which equals to 39 750 VND.

Part 3

This Part is independent of the two previous parts. There will be three Tasks in this

Part, and you will play 5 periods on each task.

At the beginning of Part 3, you will be assigned randomly into a group of two players. This group is kept the same during this Part: you will play with the same player.

In your group, you will be assigned randomly by the computer to be Player 1 or Player 2. Your role is kept for 15 periods in this Part.

You will decide on the amount of your land allocated to organic agriculture at each period; this quantity is called X.

To help you have an idea about organic agriculture, we have a definition below:

"Organic agriculture is the agricultural method that prohibits any usage of pesticides and other chemical substances, gene-modified products, and any products that originate from radiated substances. Organic agriculture reduces the negative effects of agricultural activities on the environment, such as water pollution; it also provides safe and healthy food to human beings. Organic agriculture can produce higher quality products than conventional products. People can also trace the origin of the organic products."

Your decision on the land allocated does not impact your real decision on your own land; it is just for this experiment.

In this Part,

- If you are Player 1, you decide first your land allocated to organic agriculture, we call X1.

- If you are Player 2, you receive Player 1's decision, X1. Then, you decide on your land allocated to organic agriculture, which we call X2.

Your decision X, the quantity of land allocated to organic agriculture, will create an amount of money that you gain at each period; this amount depends only on your decision.

In the experiment, there are two types of organic agriculture. One type is called High organic agriculture technology.; the other is called Low organic agriculture technology. In general, with the same land allocation to organic agriculture, you will receive higher profit under the High organic agriculture technology than from the Low organic agriculture technology.

More specifically, if the organic agriculture technology of your group is high and you choose X, your gain in VND is calculated as below:

75 000 + 160 500 * X – (100 000 * X * X)

where X is the quantity of land allocated to organic agriculture; it gets any the value from 0 to 1.

If the organic agriculture technology is low, your gain from your decision X calculated at each periods is as below

75 000 + 46 000 * X – (115 000 * X * X)

where X is the quantity of land allocated to organic agriculture; it gets any value from 0 to 1.

Under the same quantity of land used for organic agriculture, High organic agriculture yields higher gains than Low organic agriculture.

Your gain in this Part:

After playing all three tasks in this part, one player among you is chosen randomly. This player chooses randomly one decision among your 15 decisions to calculate for your gain in Part 3, knowing that all 15 decisions have the same chance to be chosen.

Now, you start to play Task 1 of this Part.

TASK 1

In this Task, your group will be in High organic agriculture technology or in Low organic agriculture technology. For convenience, we now call it High or Low. The type of organic agriculture of your group may be different to other groups because we choose randomly and independently for each group. We randomly choose again for each period in this Task.

There is a 50 percent chance that your group is in High and a 50 percent chance that your group is in Low.

You and the other players in your group know that your group is either in High organic agriculture or Low organic agriculture.

Your decision:

If you are Player 1, you decide their allocation of land to organic agriculture, X1 first.

If you are Player 2, after Player 1 decides, you receive Player 1's decision, X1, and then you decide on the allocation of land to organic agriculture, X2.

Your gain in this Task depends only on your decision. It does not depend on the decision of other Players.

Your gain

After two player decide, you receive your gain in this Period calculated from your decision

- If you are in the High organic agriculture, your gain in VND from your decision on land allocated to organic agriculture X, is

75 000 + 160 500 * X – (100 000 * X *X)

- If you are in the Low organic agriculture, your gain in VND from your decision land allocated to organic agriculture X is 75 000 + 46 000 * X – (115 000 * X *X)

Before confirming your decision, to help you in your choice X, you can see the estimated of the gain you will receive based on one of the formula above.

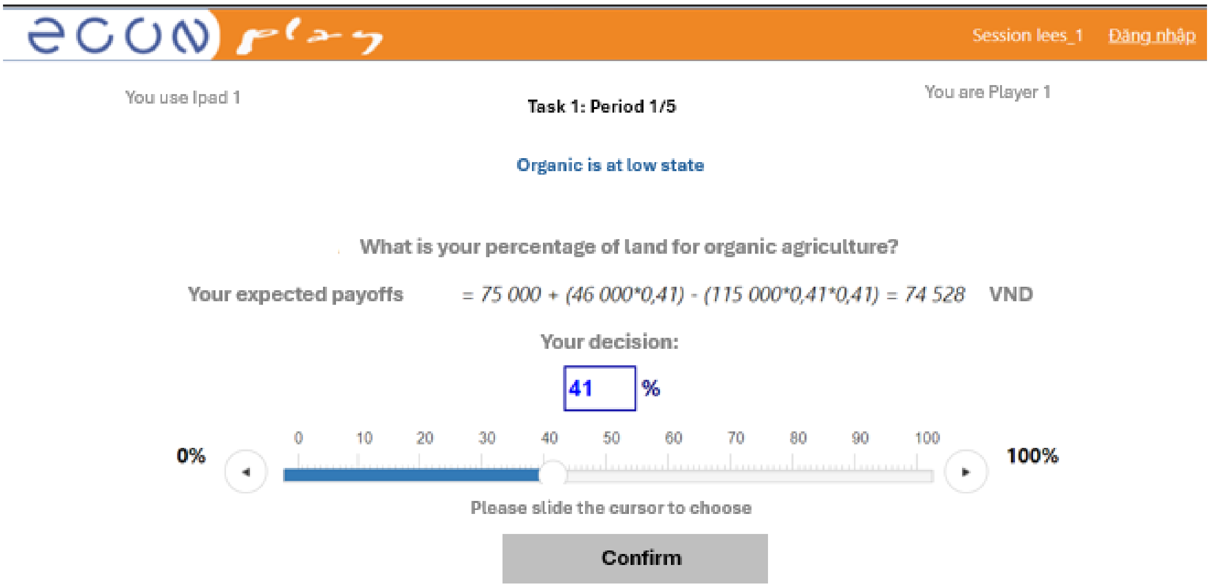


Figure 4.5: Screenshot of Task 1 in Part 3

TASK 2

Your group is kept the same as in the previous Task.

Your group will be in High organic agriculture or low organic agriculture. Your group's type of organic agriculture may be different from other groups because we choose randomly and independently for all groups. We also randomly choose again for each period in this Task.

There is a 50 percent chance that your group is in High and a 50 percent chance that your group is in Low.

In this Task, only Player 1 knows that your group is in High or Low organic agriculture.

Player 2 does not know that your group is in High or Low organic agriculture:

- If you are Player 1, you know that your group is in High or Low organic agriculture

- If you are Player 2, you do not know that your group is in High or Low organic agriculture

Your decision

If you are Player 1, you will decide on the land allocation to organic agriculture, X1.

If you are Player 2, you know Player 1's decision X1, and then you make two decisions on the land allocation to organic agriculture.

- You will make one decision on the land allocation to organic agriculture as if your group is in the High organic agriculture

- You will make one decision on the land allocation to organic agriculture as if your group is in the Low organic agriculture Your gain in this Task depends only on your decision. It does not depend on the decision of other Players.

You will play this Task for five periods.

Your gain:

After two players make decisions, you will know the type of organic agriculture that your group is in.

For Player 1, your gain is calculated from your decision X1, as in Task 1.

For Player 2, your decision corresponding to the proper type is used to calculate your gain.

- If your group is truly in High organic agriculture and you decided the land allocation of organic agriculture is XHigh for High organic agriculture, your gain in VND from your decision is calculated as

75 000 + 160 500 * XHigh – (100 000 * XHigh * XHigh)

- If your group is truly in the Low organic agriculture and you decided the land allocation of organic agriculture is Xlow for low organic agriculture, your gain in VND from your decision Xlow is calculated as

75 000 + 46 000 * XLow – (115 000 * XLow *XLow)

To help you decide, the picture below gives you the estimated gain you get from your choice under each type of organic agriculture.

TASK 3:

Your group is kept the same as your group in previous Tasks.

Your group will be in High organic agriculture or Low organic agriculture. Your

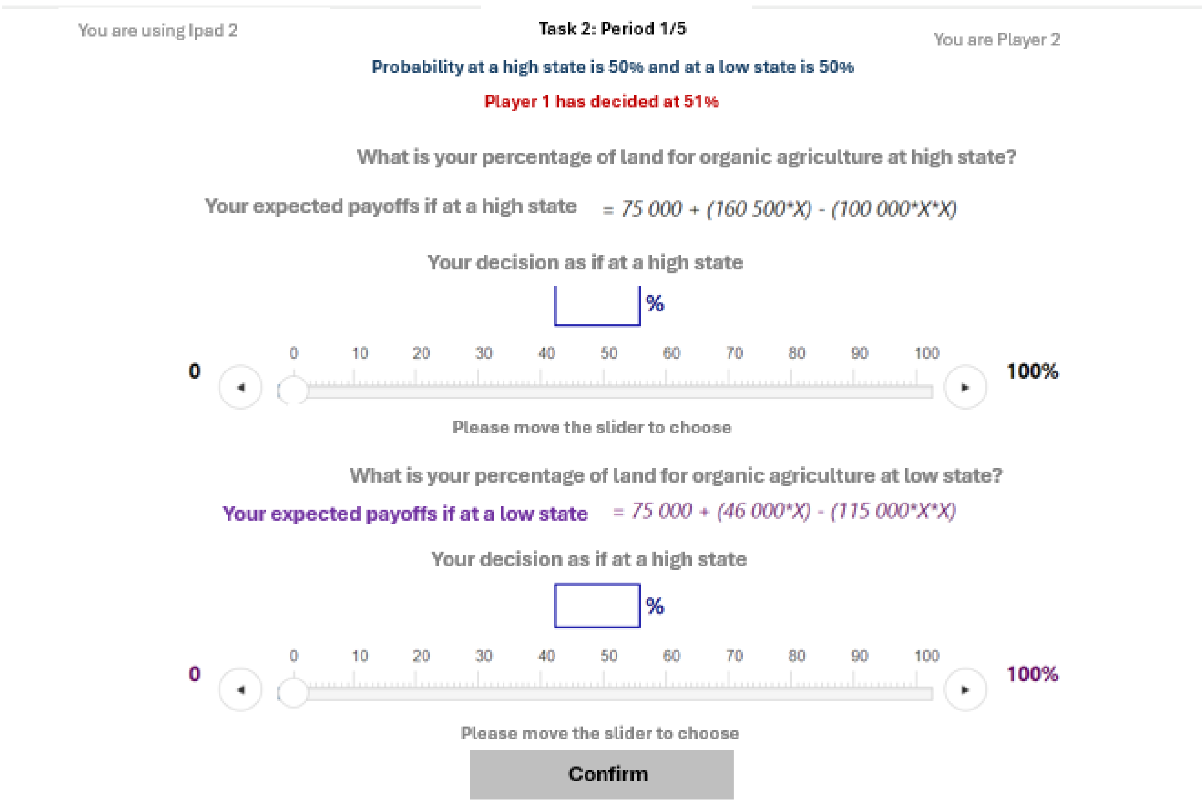


Figure 4.6: Screenshot of player 2 in Task 2 in Part 3

group's type of organic agriculture may be different from other groups because we choose randomly for all groups and again for each period in this Task.

There is a 50 percent chance that your group is in High organic agriculture and 50 percent chance that your group is in Low organic agriculture

In this Task, only Player 1 knows that your group is in High or Low organic agriculture.

Player 2 does not know that your group is in High or low organic agriculture:

- If you are Player 1, you know that your group is in High or Low organic agriculture

- If you are Player 2, you do not know that your group is in High or Low organic agriculture

In this Task, Player 1 and Player 2 can decide on their own to share the information: Player 1 can tell Player 2 that they are in High or Low organic agriculture.

With the information from Player 1, Player 2 knows that they are in organic agriculture and may receive a higher gain in VND than if Player 2 does not have the information.

Thus, Player 1 can demand that Player 2 share a percentage of the information's benefits because Player 1 helps Player 2 obtain the information.

Cooperation in the experiment is defined as a successful negotiation between Player 1 and Player 2 on information sharing and benefit sharing.

For example, if the gain that Player 2 gets without negotiation is 70 000 VND, and the highest potential gain that Player 2 gets with negotiation from Player 1 is 100 000 VND, then Player 2 can increase their highest potential gain by 100 000 VND – 70 000 VND = 30 000 VND, with the negotiation from Player 1. The amount of 30 000 VND is the benefit of the negotiation. Then, Player 1 can ask Player 2 to share a percentage of 30 000 VND; Player 2 can ask to keep a percentage of 30 000 VND.

In this Task, you and the other player communicate only through the iPad. You cannot talk face-to-face to other player.

Your decision:

You will decide in three Steps.

Step 1: Before deciding whether to negotiate or not

If you are Player 1, you decide the amount of your land allocated to organic agriculture, called X1.

If you are Player 2, you know Player 1's decision X1, and you decide your land allocated to organic agriculture. You make two decisions as in Task 2:

- You decide the land allocated to organic agriculture as if your group is in High organic agriculture

- You decide the land allocated to organic agriculture as if your group is in Low organic agriculture

Step 2: Decide whether to negotiate or not

After Step 1, you and the other player decide,

- You will decide whether you want to negotiate with another player in your group.

- The other player in your group decides that (s)he wants to negotiate with you or not.

If one or two players do not agree to negotiate, you and the other player do not negotiate with each other.

- Player 1 does not give information on the organic agriculture.

- Player 2 does not know if they are in high or low organic agriculture.

If two players agree to negotiate, you and the other players start a negotiation in Step 3.

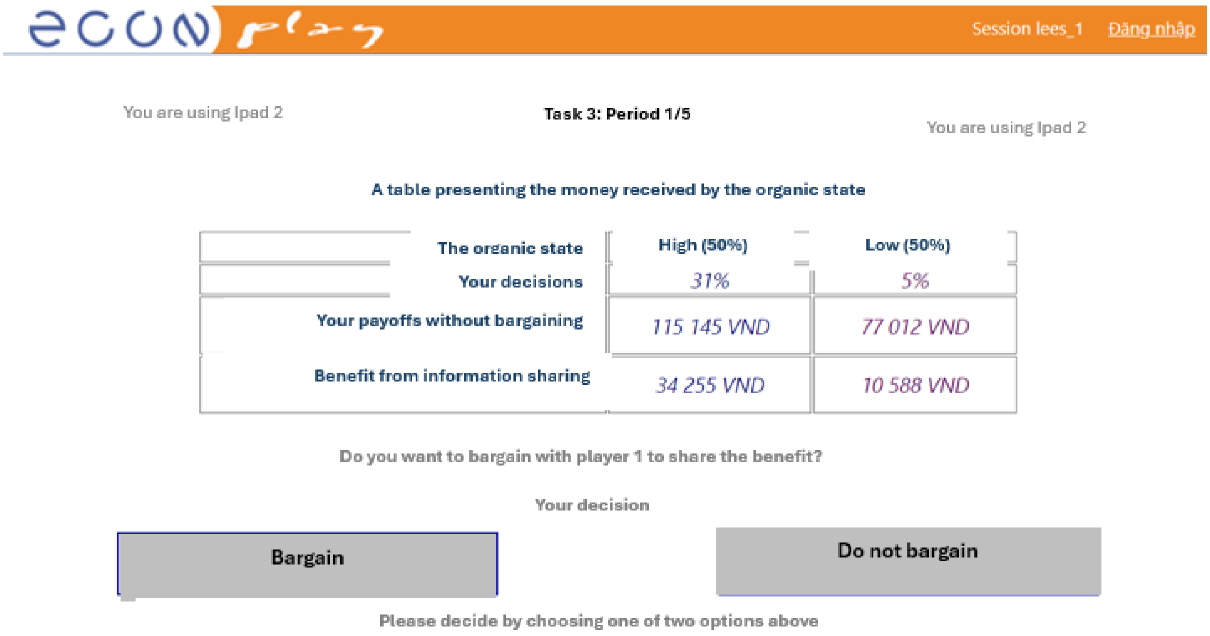


Figure 4.7: Screenshot of the decision to bargain of player 2 in Task 3, Part 3

Step 3: Negotiate

We would like to remind you that the negotiation benefit that you and the other players are going to negotiate is the difference between the highest profit that Player 2 can get with information and the profit that Player 2 can get without information and decided from Step 1.

You and other players negotiate so that

- If you are Player 1, you ask Player 2 to share a percentage of the negotiation's benefit that Player 2 will have from your cooperation.

If you are Player 2, you ask Player 1 to let you know your group's type of organic agriculture because you may get a higher gain in VND with negotiation; you demand the percentage of the cooperation benefit for you.

For example, let's imagine that you are Player 1, and you know that if Player 2 has the information, Player 2 will receive the highest information benefit GG if your group is in High organic agriculture and the highest information benefit GL if your group is in low organic agriculture. You want Player 2 to share a part of GG or GL. You can ask any percentage such as one-tenth, one-fourth, a half, three-forth, or all GG or GL. If you are Player 2, you want to keep a part of GG or GL for you. You may want to keep all or share one-tenth, one-forth, a half, or three-fourths of GG or GL for you.

The negotiation follows the rules such that:

- You and the other player propose one percentage. This percentage is the same for High organic agriculture and Low organic agriculture.

- Player 1 proposes first the percentage.

- You can send the percentage of the benefit you want for yourself, call mypercentage, from 0% to 100%, it can have the decimal part too. Then, the percentage of benefit that other player can get is 1 - mypercentage.

- Player 2 can accept or refuse your proposal.

o If the Player 2 accepts, the negotiation end with an agreement.

o If the Player 2 refuses, they can send their percentage.

- When you receive a proposal from other player, you can accept or refuse.

o If you accept, the negotiation ends with an agreement.

o If you refuse, you can send another proposal

- After the seventh proposals:

o If the next proposal is accepted, the negotiation ends with an agreement

o If the next proposal is refused, there are 50% chance that the negotiation continues normally and 50% chance that the negotiations ends without an agreement

You will use the Ipad to send the proposal. There are not right or wrong proposals. You and the other player are free to negotiate.

Your gain:

If you and other player do not negotiate or the negotiation ends without an agreement, your gain will be calculated from your decision in Step 1.

If you are Player 1, you decided in Step 1 the amount of land allocated to organic agriculture is X1, then

- If your group is in the High organic agriculture, your gain in VND from your decision X1 is

75 000 + 160 500 x X1 – (100 000 x X1 x X1)

- If your group is in the Low organic agriculture, your gain in VND from your decision X1 is

75 000 + 46 000 * X1 – (115 000 x X1 * X1)

If you are Player 2, you decide in Step 1 that you choose X2G is the amount of land allocated to organic agriculture as if you are in High organic agriculture and you choose X2B is the amount of land allocated to organic agriculture as if you are in Bad organic agriculture, then

- If your group is in the High organic agriculture, your gain in VND from your decision X2G is

75 000 + 160 500 x X2G – (100 000 x X2G x X2G)

- If your group is in the Low organic agriculture, your gain in VND from your decision X2B is

75 000 + 46 000 * X2B – (115 000 x X2B x X2B)

If the negotiation end with an agreement, you and other player agree on the percentage mypercentage for you and 1-mypercentage for the other

If you are Player 1, your gain is your gain calculated in Step 1 plus the share of benefit from negotiation

- If your group is in the High organic agriculture, your gain in VND from your decision X1 is

85 000 + 160 500 x X1 – (100 000 x X1 x X1) + mypercentage x GG

- If your group is in the Low organic agriculture, your gain in VND from your decision X1 is

85 000 + 46 000 * X – (115 000 x X1 x X1) + mypercentage * GL

If you are Player 2, your gain calculated in Step 1 plus the share of benefit from negotiation

- If you are in the High organic agriculture, your gain in VND from your decision X2G is

85 000 + 160 500 * X2G – (100 000 x X2G x X2G) + mypercentage x GG

- If you are in the Low organic agriculture, your gain in VND from your decision X2B is

85 000 + 46 000 x X2B – (115 000 x X2B x X2B) + mypercentage x GL

We would like to remind that:

After playing all three Tasks of this Part, one player among you is chosen randomly. This player chooses randomly one decision among your 15 decisions to calculate for your gain in Part 3, knowing that all 15 decisions have the same chance to be chosen.

General conclusion

The primary object of this thesis is to examine the social factors influencing the adoption of organic agriculture. We derived and answered the central questions in the above-mentioned chapters to realize this objective. Each chapter analyzed comprehensively a group of factors (social norms in Chapter 1; the training and technical advice, sales contract, certification and traceability, neighbors, and leadership in Chapter 2; leadership and information sharing in Chapter 3 and Chapter 4) and applied respectively a different economic analysis to answer its question: meta-analysis regression; field experiment with discrete choice experience; theoretical model; and field experiment with Nash-bargaining game.

We conducted experiments with Northern Vietnamese farmers to build a concrete data set about the farmer's decisions. The uniqueness of our data set is an important point that we contribute to the current literature. The other main contribution lies in applying the *Nash-bargaining model* as an information-sharing solution between farmers powered by experimental analysis. This may be a reference for designing and implementing contextualized lab-in-field experiments with farmers. It is one of the first studies to propose a theoretical building for lab-in-field experiments using Nash bargaining in organic agriculture.

Each chapter's findings contributed to the knowledge of adopting organic agriculture. In Chapter 1, we employed meta-regression analysis to assess the influence of social norms on the adoption of organic food, aiming to establish a robust and consistent conclusion regarding the role of social influences as incentives for consuming organic products. We gathered data from 41 papers across various journals, totaling 122 observations, all investigating the relationship between social influence and organic food adoption. The study found no discernible trend in the dissemination effect size attributable to bias. By relying on the estimated effect sizes from the meta-analysis, we could conclude that a moderate-positive relationship exists between social norms and the adoption of organic food. Thus, consumer behavior toward organic food is undeniably shaped by the views, opinions, and behaviors of others (Ajzen, 1991). As such, researchers and policymakers can leverage this understanding to develop appropriate tools and incentives to promote organic food adoption. Research also suggests that subjective norms influence consumers' behavior more than descriptive norms do. Therefore, policies regarding organic food may be less effective if they fail to adequately consider social acceptance in consumer opinion. Leveraging the descriptive norm with subjective or injunctive norm can yield more efficient outcomes in altering pro-social behavior, particularly in organic food choice. We found that the concern for health regarding food consumption emerges as a crucial factor influencing the selection of organic food (see Table 1.5). Individuals generally hold a positive perception of the health benefits associated with organic food, which motivates purchasing such products (Khare, 2015; Klöckner and Ohms, 2009). These results have paved the way for future policies to leverage social influences to create consumer incentives.

Chapter 2 introduces the essential attributes that farmers could consider when choosing to be at the status quo or follow a new agricultural practice. We aim to understand what motivates farmers in Northern Vietnam to choose organic agriculture. Our study involves surveying 586 farmers using a quantitative method called a discrete choice experiment. We analyzed how different factors impact farmers' decisions to adopt organic farming by assessing market-related factors, like sales, contracts, and organic logos, as well as non-market factors, such as training sessions and local support. Additionally, we examined the influence of community factors like coordination with neighbors and the presence of organic farming leaders in villages. Our findings indicated that the attributes above significantly influence farmers' choices regarding participation in organic certification programs. The chapter revealed that sales contracts offering flexible or guaranteed prices are significant incentives, motivating farmers to accept higher production costs associated with participating in organic certification schemes. Secondly, the attribute of ”traceability” is also crucial in driving the adoption of organic certification. Farmers often need a logo with a traceable code to secure a sales contract, which signifies that their organic products have undergone rigorous quality checks and production monitoring systems. Thirdly, offering training and technical support to farmers through village leaders or the president of the farmers’ association, acting as public extension agents, could prove highly effective in driving the adoption of organic farming. Our observations suggested that farmers in the surveyed areas place significant importance on the involvement of their formal leaders in organic farming activities. We also observed that promoting neighborhood cooperatives instead of solely focusing on individual farmers could be a more practical approach to encouraging farmers to transition to organic farming practices. Then, education, training, and access to information regarding organic farming standards, technologies, and practices are vital for farmers. These resources help enhance their knowledge and capacity to adopt sustainable farming practices, engage in organic agricultural production, and navigate new market dynamics. The study’s results confirmed that rice producers are willing to incur higher production costs if formal leaders or both formal and informal leaders in their villages are engaged in organic farming initiatives.

One of our findings in chapter 2 is that a leader’s decisions played a role in farmer’s decisions. The mechanism explaining the relationship between leadership and farmers’ decision to adopt organic agriculture needs further analysis, so we aimed to investigate more this problem in chapter 3. We set up a model in which farmers confront the dilemma of transitioning their land to a new agricultural type while lacking sufficient information to ensure the ultimate benefits of their decisions. This model introduced the concept of the ”first-mover” who possesses complete information: observing the actions of the first-mover allows contributors to optimize their choices and attain the maximum benefit. We integrated Nash’s bargaining model to solve the problem of sharing information. Our model firstly indicated that risk-averse farmers allocate at a lower level than other types of farmers, and their allocation is not optimal. This causes a loss to farmers and society, which requires a higher adoption area for organic agriculture. We then showed a positive gain from sharing information about organic agriculture like BenYishay and Mobarak (2019). The model predicts that all farmers will join the bargaining step to find an agreement to share information and maximize their payoffs. We proved that the bargaining share depends on the bargaining power of the leader and follower. This model supplied the principal framework for the design of the lab-in-field experiment in Chapter 4.

In Chapter 4, we designed a lab-in-field experiment to examine the Vietnamese farmer's decision on organic agriculture under our theoretical model in Chapter 3. In our experiment, we observed an interaction between two farmers who determine the allocation of their lands between conventional and organic agriculture. Both farmers confronted the same production function and associated risks. One of the farmers was designated as the "leader," defined as the individual possessing equal or superior information compared to the other farmer and consistently making decisions first. This definition of a leader aligns with studies on information sharing in social contexts (Garfield et al., 2020). There are three scenarios for the farmers' decision-making process: (1) both farmers receive identical information, (2) the leader receives superior information, and (3) the leader receives superior information, and both farmers have the option to share information. Information sharing was modeled according to the Nash-Bargaining model (Nash, 1953), facilitating the construction of a cooperative game between the two farmers by outlining the benefits of sharing information. The study's findings corroborated this prediction: farmers engaging in bargaining in scenario 3. There was a high demand among farmers for information-seeking when navigating agricultural risks. The model aligned well with empirical studies indicating that farmers are more inclined to seek information from other farmers within their communities (Bakker et al., 2021).

Moreover, informed farmers play a crucial role in disseminating information and influencing the adoption of new practices, such as organic agriculture. These results advocated an approach to information diffusion policies prioritizing promoting organic agriculture over traditional methods like extension services. This chapter demonstrated that farmers' social value orientation significantly influences their agreed-upon share. Leaders with a competitive social orientation notably increased their bargaining demands. Additionally, the study highlighted the role of "Prosocial" orientation in the bargaining model, where the group's benefit of reaching an agreement becomes valuable to players, motivating them to lower their propositions to mitigate the risk of disagreement. These findings underscore the importance of expanding our model to incorporate non-monetary incentives in cooperation and information sharing.

To conclude, this thesis helped us clarify our primary objective of how social factors impact the adoption of organic agriculture. Throughout the chapters, we have explicitly stated the different hurdles farmers encounter if they consider investing in this new practice so that policymakers can consider proposing an appropriate policy. For instance, farmers prefer having the training to do organic farming, a system to certify their organic products and trace them easily. Thus, those results support a policy's development that is aligned with the farmer's needs. According to our results, policymakers can focus on how to boost the adoption level through the neighbor's effects found in our study. We also saw that farmers need information to decide. Our Nash-bargaining model showed that farmers voluntarily join a negotiation with leaders to share information. After the bargaining, farmers honor their duties (followers give the leaders their benefits from information), but in the actual context, how are we sure about farmers' commitments to fulfill their duties? From this point of view, the policymaker could play a role in facilitating the information-sharing process about farmers and ensuring the commitment of both parties. Besides, the experimental designs in our thesis may contribute to developing other experimental studies in organic agriculture.

Conclusion générale

L'objectif principal de cette thèse est d'examiner les facteurs sociaux qui influencent l'adoption de l'agriculture biologique. Nous avons dérivé et répondu à quatre questions principales dans les chapitres mentionnés ci-dessus pour réaliser cet objectif. Chaque chapitre analyse de manière exhaustive un groupe de facteurs (les normes sociales dans le chapitre 1; la formation et les conseils techniques, le contrat de vente, la certification et la traçabilité, les voisins et le leadership dans le chapitre 2; leadership et partage d'information dans le chapitre 3 and Chapter 4) et a appliqué respectivement une analyse économique différente pour répondre à sa question: régression méta-analyse ; expérience sur le terrain avec expérience de choix discret ; modèle théorique ; et expérience sur le terrain avec jeu de négociation de Nash.

Nous avons mené des expériences avec des agriculteurs du Nord-Vietnam pour construire un ensemble de données concrètes sur les décisions des agriculteurs. Le caractère unique de notre ensemble de données est un point important que nous apportons à la littérature actuelle. L'autre contribution principale réside dans l'application du *Nash-bargaining model* comme une solution de partage d'informations entre les agriculteurs, alimentée par des analyses expérimentales. Cela peut servir de référence pour la conception et la mise en œuvre d'expériences contextualisées de laboratoire sur le terrain avec des agriculteurs. Il s'agit de l'une des premières études à proposer un bâtiment théorique pour des expériences en laboratoire sur le terrain utilisant la négociation de Nash dans l'agriculture biologique. Les résultats de chaque chapitre ont contribué à la connaissance de l'adoption de l'agriculture biologique:

Dans le chapitre 1, nous utilisons une analyse de méta-régression pour évaluer l'influence des normes sociales sur l'adoption d'aliments biologiques, dans le but d'établir une conclusion robuste et cohérente concernant le rôle des influences sociales comme incitatifs à la consommation de produits biologiques. Nous avons recueilli des données dans 41 articles de divers journaux, totalisant 122 observations, toutes examinant la relation entre l'influence sociale et l'adoption d'aliments biologiques. Nous affirmons qu'il n'y a pas de tendance perceptible dans la taille de l'effet de diffusion attribuable au biais. En se basant sur les tailles d'effet estimées de la méta-analyse, nous avons pu conclure qu'il existe une relation modérément positive entre les normes sociales et l'adoption des aliments biologiques. Le comportement des consommateurs envers les aliments biologiques est indéniablement façonné par les points de vue, les opinions et les comportements des autres (Ajzen, 1991). Les chercheurs et les décideurs peuvent donc tirer parti de cette compréhension pour élaborer des outils et des mesures d'incitation appropriés afin de promouvoir l'adoption des aliments biologiques. La recherche suggère que les normes subjectives influencent le comportement des consommateurs plus que les normes descriptives. Cela implique que l'influence des opinions des autres l'emporte sur l'impact des comportements observés. Par conséquent, les politiques relatives aux aliments biologiques peuvent être moins efficaces si elles ne tiennent pas compte de manière adéquate des tendances dans l'opinion des consommateurs. Le fait de mettre à profit la norme descriptive avec une norme subjective ou injonctive peut produire des résultats plus efficaces en modifiant le comportement prosocial, particulièrement dans le choix d'aliments biologiques. Nous avons constaté que la préoccupation pour la santé en ce qui concerne la consommation alimentaire apparaît comme un facteur crucial influençant le choix des aliments biologiques (voir tableau 1.5). Les individus ont généralement une perception positive des bienfaits pour la santé associés aux aliments biologiques, ce qui motive l'achat de ces produits (Khare, 2015; Klöckner and Ohms, 2009). Ces résultats ouvrent la voie à des politiques futures visant à tirer parti des influences sociales pour créer des incitations à l'intention des consommateurs.

Le chapitre 2 présente les attributs essentiels que les agriculteurs pourraient prendre en compte lorsqu'ils choisissent de rester au statu quo ou de suivre une nouvelle pratique agricole. Nous cherchons à comprendre ce qui motive les agriculteurs du nord du Vietnam à choisir l'agriculture biologique. Notre étude porte sur 586 agriculteurs et agricultrices, selon une méthode quantitative appelée expérience de choix discret. Nous analysons l'impact de différents facteurs sur les décisions des agriculteurs d'adopter l'agriculture biologique en évaluant les facteurs liés au marché, comme les ventes, les contrats et les logos biologiques, ainsi que les facteurs non commerciaux, tels que les sessions de formation et le soutien local. Nous examinons également l'influence de facteurs communautaires tels que la coordination avec les voisins et la présence de dirigeants d'exploitations biologiques dans les villages. Nos résultats indiquent que chacun des attributs susmentionnés influence de façon significative les choix des agriculteurs en ce qui concerne la participation aux programmes de certification biologique. Le chapitre révèle que les contrats de vente offrant des prix flexibles ou garantis sont d'importantes incitations, motivant les agriculteurs à accepter des coûts de production plus élevés associés à la participation aux systèmes de certification biologique. Deuxièmement, l'attribut de la "traçabilité" est également crucial pour favoriser l'adoption de la certification biologique. Les agriculteurs ont souvent besoin d'un logo avec un code traçable pour obtenir un contrat de vente, ce qui signifie que leurs produits biologiques ont subi des contrôles de qualité rigoureux et des systèmes de contrôle de la production. Troisièmement, offrir une formation et un soutien technique aux agriculteurs par l'intermédiaire des dirigeants de village ou du président de l'association d'agriculteurs, agissant en tant qu'agents publics de vulgarisation, pourrait s'avérer très efficace pour favoriser l'adoption de l'agriculture biologique. Nos observations suggèrent que les agriculteurs des zones étudiées accordent une importance significative à l'implication de leurs dirigeants officiels dans les activités d'agriculture biologique. Nous avons également observé que la promotion des coopératives de quartier au lieu de se concentrer uniquement sur les agriculteurs individuels pourrait être une approche plus pratique pour encourager les agriculteurs à passer aux pratiques agricoles biologiques. Ensuite, l'éducation, la formation et l'accès à l'information sur les normes, les technologies et les pratiques de l'agriculture biologique sont essentiels pour les agriculteurs. Ces ressources aident à améliorer leurs connaissances et leur capacité d'adopter des pratiques agricoles durables, de s'engager dans la production agricole biologique et de naviguer dans les nouvelles dynamiques du marché. Les résultats de l'étude confirment que les producteurs de riz sont prêts à supporter des coûts de production plus élevés si les dirigeants officiels ou les dirigeants officiels et informels de leurs villages s'engagent dans des initiatives d'agriculture biologique.

Une de nos constatations dans le chapitre 2 est que les décisions d'un chef ont joué un rôle dans les décisions des agriculteurs. Le mécanisme expliquant la relation entre les dirigeants et la décision des agriculteurs d'adopter l'agriculture biologique nécessite une analyse plus approfondie, nous avons donc cherché à étudier davantage ce problème. Au chapitre 3, nous avons mis en place un modèle dans lequel les agriculteurs sont confrontés au dilemme de passer à un nouveau type d'agriculture, sans disposer d'informations suffisantes pour garantir les bénéfices ultimes de leurs décisions. Le modèle introduit le concept du "premier venu" qui possède une information complète. Observer les actions des premiers contributeurs permet d'optimiser leurs choix et d'en tirer le maximum de bénéfices. Nous intégrons le modèle de négociation de Nash pour résoudre le problème du partage d'information. Notre modèle indique d'abord que les agriculteurs qui sont peu enclins au risque allouent à un niveau inférieur à celui des autres types d'agriculteurs, et leur allocation n'est pas optimale. Cela entraîne une perte pour les agriculteurs et la société, ce qui nécessite une zone d'adoption plus élevée pour l'agriculture biologique. Nous montrons ensuite un gain positif en partageant des informations sur l'agriculture biologique comme BenYishay and Mobarak (2019). Le modèle prévoit que tous les agriculteurs se joindront à l'étape de négociation pour trouver une entente afin de partager l'information et de maximiser leurs gains. Nous avons démontré que la part de négociation dépend du pouvoir de négociation du leader et du suiveur. Ce modèle fournit le cadre principal pour la conception de l'expérience en laboratoire sur le terrain dans le chapitre 4.

Dans le chapitre 4, nous concevons une expérience de laboratoire sur le terrain pour examiner la décision des agriculteurs vietnamiens sur l'agriculture biologique dans notre modèle théorique du chapitre 3. Dans notre expérience, on observe une interaction entre deux agriculteurs qui déterminent la répartition de leurs terres entre l'agriculture conventionnelle et l'agriculture biologique. Les deux agriculteurs sont confrontés à la même fonction de production et aux risques qui y sont associés. L'un des agriculteurs est désigné comme ≪ leader ≫, c'est-à-dire la personne qui possède les mêmes renseignements ou des renseignements supérieurs que l'autre agriculteur et qui prend systématiquement les premières décisions. Cette définition du leader s'harmonise avec les études sur le partage de l'information dans des contextes sociaux (Garfield et al., 2020). Les chercheurs ont décrit trois scénarios pour le processus décisionnel des agriculteurs : (1) les deux agriculteurs reçoivent des informations identiques, (2) le leader reçoit des informations supérieures et (3) le leader reçoit des informations supérieures, et les deux agriculteurs ont la possibilité de partager l'information. Le partage de l'information est modélisé selon le modèle de Nash-Bargaining (Nash, 1953), faciliter la construction d'un jeu de coopération entre les deux agriculteurs en soulignant les avantages du partage de l'information. Les résultats de l'étude corroborent cette prédiction : les agriculteurs négocient dans le scénario 3. Il y a une forte demande parmi les agriculteurs pour la recherche d'information lorsqu'ils gèrent les risques agricoles. Le modèle s'harmonise bien avec les études empiriques qui indiquent que les agriculteurs sont plus enclins à demander de l'information aux autres agriculteurs au sein de leur collectivité (Bakker et al., 2021).

En outre, les agriculteurs informés jouent un rôle crucial dans la diffusion de l'information et influencent l'adoption de nouvelles pratiques, telles que l'agriculture biologique. Ces résultats préconisent une approche des politiques de diffusion de l'information qui privilégie la promotion de l'agriculture biologique par rapport aux méthodes traditionnelles comme les services de vulgarisation. Ce chapitre démontre que l'orientation vers la valeur sociale des agriculteurs influence de façon significative leur part convenue. Les leaders ayant une orientation sociale concurrentielle affichent une augmentation notable de leurs demandes en matière de négociation. De plus, l'étude met en évidence le rôle de l'orientation "prosociale" dans le modèle de négociation, où l'avantage du groupe à parvenir à un accord devient précieux pour les acteurs, les motivant à baisser leurs propositions afin d'atténuer le risque de désaccord. Ces résultats soulignent l'importance d'élargir notre modèle pour y inclure des incitations non monétaires à la coopération et au partage de l'information.

Pour conclure, cette thèse nous a permis de clarifier notre objectif premier sur la façon dont les facteurs sociaux influencent l'adoption de l'agriculture biologique. Tout au long des chapitres, nous indiquons explicitement les différents obstacles auxquels se heurtent les agriculteurs lorsqu'ils envisagent d'investir dans cette nouvelle pratique afin que les décideurs politiques puissent envisager de proposer une politique appropriée. Par exemple, les agriculteurs préfèrent avoir la formation pour faire de l'agriculture biologique, un système pour certifier leurs produits biologiques et les suivre facilement. Ainsi, ces résultats appuient l'élaboration d'une politique qui est alignée sur les besoins de l'agriculteur. Selon nos résultats, les décideurs peuvent se concentrer sur la façon d'accroître le niveau d'adoption grâce aux effets du voisin que nous avons trouvés dans notre étude. Nous avons également constaté que les agriculteurs ont besoin d'information pour prendre des décisions. Notre modèle de négociation de Nash a montré que les agriculteurs se joignent volontairement à une négociation avec des leaders pour partager l'information. Après la négociation, les agriculteurs honorent leurs devoirs (les adeptes donnent aux dirigeants leurs avantages de l'information), mais dans le contexte réel, comment pouvons-nous être sûrs que les agriculteurs s'engagent à remplir leurs devoirs? De ce point de vue, le décideur politique pourrait jouer un rôle en facilitant le processus d'échange d'informations sur les agriculteurs et en assurant l'engagement des deux parties. En outre, les conceptions expérimentales de notre thèse peuvent contribuer au développement d'autres études expérimentales dans l'agriculture biologique.

Bibliography

Aarset, B., Beckmann, S., Bigne, E., Beveridge, M., Bjorndal, T., Bunting, J., McDonagh, P., Mariojouls, C., Muir, J., Prothero, A., et al. (2004). The european consumers' understanding and perceptions of the "organic" food regime: the case of aquaculture. *British food journal*, *106*(2), 93–105.

Acs, S., Berentsen, P., Huirne, R., & Van Asseldonk, M. (2009). Effect of yield and price risk on conversion from conventional to organic farming. *Australian Journal of Agricultural and Resource Economics*, *53*(3), 393–411.

Adebayo, S. A., & Oladele, O. I. (2013). Vegetable farmers' attitude towards organic agriculture practices in South Western Nigeria. *Journal of Food, Agriculture and Environment*, *11*(2), 548–552.

Aertsens, J., Verbeke, W., Mondelaers, K., & Van Huylenbroeck, G. (2009a). Personal determinants of organic food consumption: A review. *British Food Journal*, *111*, 1140–1167.

Aertsens, J., Verbeke, W., Mondelaers, K., & Van Huylenbroeck, G. (2009b). Personal determinants of organic food consumption: a review. *British food journal*, *111*(10), 1140–1167.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Process*, *50*, 179–211.

Albersmeier, F., Schulze, H., & Spiller, A. (2009). Evaluation and reliability of the organic certification system: perceptions by farmers in Latin America. *Sustainable Development*, *17*(5), 311–324.

Alemu, M. H., Mørkbak, M. R., Olsen, S. B., & Jensen, C. L. (2013). Attending to the reasons for attribute non-attendance in choice experiments. *Environmental and Resource Economics*, *54*, 333–359.

Al-Swidi, A., Huque, S. M. R., Hafeez, M. H., Shariff, M. N. M., Mohammed Rafiul Huque, S., Haroon Hafeez, M., & Noor Mohd Shariff, M. (2014). The role of subjective norms in theory of planned behavior in the context of organic food consumption. *British Food Journal*, *116*(10), 1561–1580.

Altenbuchner, C., Vogel, S., & Larcher, M. (2018). Social, economic and environmental impacts of organic cotton production on the livelihood of smallholder farmers in Odisha, India. *Renewable Agriculture and Food Systems*, *33*(4), 373–385.

Altobelli, F., Monteleone, A., Cimino, O., Dalla Marta, A., Orlandini, S., Trestini, S., Toulios, L., Nejedlik, P., Vucetic, V., Cicia, G., et al. (2019). Farmers' willingness to pay for an environmental certification scheme: promising evidence for water saving. *Outlook on Agriculture*, *48*(2), 136–142.

Anastasopoulos, P. C., & Mannering, F. L. (2011). An empirical assessment of fixed and random parameter logit models using crash-and non-crash-specific injury data. *Accident Analysis & Prevention*, *43*(3), 1140–1147.

Arvola, A., Vassallo, M., Dean, M., Lampila, P., Saba, A., Lähteenmäki, L., & Shepherd, R. (2008). Predicting intentions to purchase organic food: The role of affective and moral attitudes in the Theory of Planned Behaviour. *Appetite*, *50*(2-3), 443–454.

Axsen, J., Orlebar, C., & Skippon, S. (2013). Social influence and consumer preference formation for pro-environmental technology: The case of a UK workplace electric-vehicle study. *Ecological Economics*, *95*, 96–107.

Bakker, L., Sok, J., Van Der Werf, W., & Bianchi, F. (2021). Kicking the habit: what makes and breaks farmers' intentions to reduce pesticide use? *Ecological Economics*, *180*, 106868.

Barton, G. A. (2018). *The global history of organic farming*. Oxford University Press.

Bax, L., & Moons, K. G. (2011). Beyond publication bias. *Journal of Clinical Epidemiology*, *64*(5), 459–462.

Beaman, L., BenYishay, A., Magruder, J., & Mobarak, A. M. (2021). Can network theory-based targeting increase technology adoption? *American Economic Review*, *111*(6), 1918–43.

Bellemare, M. F., & Lim, S. (2018). In all shapes and colors: Varieties of contract farming. *Applied Economic Perspectives and Policy*, *40*(3), 379–401.

Bellemare, M. F., & Novak, L. (2017). Contract farming and food security. *American Journal of Agricultural Economics*, *99*(2), 357–378.

Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D. S., et al. (2002). Hybrid choice models: Progress and challenges. *Marketing Letters*, *13*(3), 163–175.

Bengtsson, J., Ahnstrom, J., & Weibull, A.-C. (2005). The effects of organic agriculture on biodiversity and abundance: a meta-analysis. *Journal of applied ecology*, *42*(2), 261–269.

Benos, N., & Zotou, S. (2014). Education and Economic Growth: A Meta-Regression Analysis. *World Development*, *64*, 669–689.

BenYishay, A., & Mobarak, A. M. (2019). Social learning and incentives for experimentation and communication. *The Review of Economic Studies*, *86*(3), 976–1009.

Berg, H. (2002). Rice monoculture and integrated rice-fish farming in the Mekong Delta, Vietnam - Economic and ecological considerations. *Ecological Economics*, *41*(1), 95–107.

Berg, H., & Tam, N. T. (2018). Decreased use of pesticides for increased yields of rice and fish-options for sustainable food production in the Mekong Delta. *Science of the Total Environment*, *619-620*, 319–327.

Bessette, D., Zwickle, S., & Wilson, R. (2019). In the weeds: Distinguishing organic farmers who want information about ecological weed management from those who need it. *Renewable Agriculture and Food Systems*, *34*(5), 460–471.

Biel, A., Dahlstrand, U., & Grankvist, G. (2005). Habitual and value-guided purchase behavior. *Ambio: a journal of the human environment*, *34*(4), 360–365.

Bolduc, D., & Alvarez-Daziano, R. (2010). On estimation of hybrid choice models. In *Choice Modelling: The State-of-the-art and The State-of-Practice*. Emerald Group Publishing Limited.

Bolwig, S., Gibbon, P., & Jones, S. (2009). The economics of smallholder organic contract farming in tropical Africa. *World Development*, *37*(6), 1094–1104.

Bontemps, C., Bougherara, D., & Nauges, C. (2021). Do risk preferences really matter? the case of pesticide use in agriculture. *Environmental Modeling & Assessment*, *26*, 609–630.

Borenstein, M., Higgins, J. P., Hedges, L. V., & Rothstein, H. R. (2017). Basics of meta-analysis: I2 is not an absolute measure of heterogeneity. *Research Synthesis Methods*, *8*(1), 5–18.

Borghino, N., Wissinger, L., Erb, K.-H., Le Mouël, C., & Nesme, T. (2024). Organic farming expansion and food security: a review of foresight modeling studies. *Global Food Security*, *41*, 100765.

Bougherara, D., Gassmann, X., Piet, L., & Reynaud, A. (2017). Structural estimation of farmers' risk and ambiguity preferences: a field experiment. *European Review of Agricultural Economics*, *44*(5), 782–808.

Boun My, K., Nguyen-Van, P., Kim Cuong Pham, T., Stenger, A., Tiet, T., & To-The, N. (2022). Drivers of organic farming: lab-in-the-field evidence of the role of social comparison and information nudge in networks in vietnam. *Ecological Economics*, *196*, 107401.

Brock, C. C., & Barham, B. L. (2013). 'Milk is milk': Organic dairy adoption decisions and bounded rationality. *Sustainability*, *5*(12), 5416–5441.

Brodeur, A., & Sangnier, M. (2016). Star Wars : The Empirics Strike Back Star Wars. *American Economic Journal: Applied Economics*, *33*(8), 1–32.

Chakravarty, S., & Roy, J. (2009). Recursive expected utility and the separation of attitudes towards risk and ambiguity: an experimental study. *Theory and Decision*, *66*, 199–228.

Charness, G., Gneezy, U., & Kuhn, M. A. (2012). Experimental methods: between-subject and within-subject design. *Journal of economic behavior & organization*, *81*(1), 1–8.

Chèze, B., David, M., & Martinet, V. (2020a). Understanding farmers' reluctance to reduce pesticide use: A choice experiment. *Ecological Economics*, *167*, 106349.

Chèze, B., David, M., & Martinet, V. (2020b). Understanding farmers' reluctance to reduce pesticide use: a choice experiment. *Ecological Economics*, *167*, 106349.

Chouichom, S., Yamao, M., et al. (2010). Comparing opinions and attitudes of organic and non-organic farmers towards organic rice farming system in North-Eastern Thailand. *Journal of Organic Systems*, *5*(1), 25–35.

Cialdini, R. B., Demaine, L. J., Sagarin, B. J., Barrett, D. W., Rhoads, K., & Winter, P. L. (2006). Managing social norms for persuasive impact. *Social Influence*, *1*(1), 3–15.

Cialdini, R. B., Reno, R. R., & Kallgren, C. A. (1990). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of Personality and Social Psychology*, *58*(6), 1015–1026.

Cialdini, R. B., & Trost, M. R. (1975). Social influence_social norms, confirmity, and compliance. In D. Gilbert, S. T. Fisk, & L. Lindzey (Eds.), *The handbook of social psychology* (pp. 151–192). McGraw-Hill House.

Činjarević, M., Agić, E., & Peštek, A. (2019). When Consumers are in Doubt, You Better Watch Out! The Moderating Role of Consumer Skepticism and Subjective Knowledge in the Context of Organic Food Consumption. *Zagreb International Review of Economics and Business*, *21*(s1), 1–14.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*(3), 297–334.

Crowder, D. W., Northfield, T. D., Strand, M. R., & Snyder, W. E. (2010). Organic agriculture promotes evenness and natural pest control. *Nature*, *466*(7302), 109–112.

Crowder, D. W., & Reganold, J. P. (2015). Financial competitiveness of organic agriculture on a global scale. *Proceedings of the National Academy of Sciences*, *112*(24), 7611–7616.

Cui, Z., Zhang, H., Chen, X., Zhang, C., Ma, W., Huang, C., Zhang, W., Mi, G., Miao, Y., Li, X., et al. (2018). Pursuing sustainable productivity with millions of smallholder farmers. *Nature*, *555*, 363–366.

Daly, A., Hess, S., Patruni, B., Potoglou, D., & Rohr, C. (2012). Using ordered attitudinal indicators in a latent variable choice model: A study of the impact of security on rail travel behaviour. *Transportation*, *39*(2), 267–297.

Darnhofer, I., Schneeberger, W., & Freyer, B. (2005). Converting or not converting to organic farming in Austria: Farmer types and their rationale. *Agriculture and Human Values*, *22*(1), 39–52.

Daxini, A., O'Donoghue, C., Ryan, M., Buckley, C., Barnes, A. P., & Daly, K. (2018). Which factors influence farmers' intentions to adopt nutrient management planning? *Journal of Environmental Management*, *224*, 350–360.

De Ponti, T., Rijk, B., & Van Ittersum, M. K. (2012). The crop yield gap between organic and conventional agriculture. *Agricultural systems*, *108*, 1–9.

Di Falco, S., Doku, A., & Mahajan, A. (2020). Peer effects and the choice of adaptation strategies. *Agricultural Economics*, *51*(1), 17–30.

Dimitri, C., & Baron, H. (2019). Private sector support of the farmer transition to certified organic production systems. *Organic Agriculture*, *10*, 261–276.

Dinh, N. C., Mizunoya, T., Ha, V. H., Hung, P. X., Tan, N. Q., & An, L. T. (2023). Factors influencing farmer intentions to scale up organic rice farming: preliminary findings from the context of agricultural production in Central Vietnam. *Asia-Pacific Journal of Regional Science*, *7*(3), 749–774.

Doucouliagos, C. (2005). Publication Bias in the Economic Freedom and Economic Growth Literature. *Journal of Economic Surveys*, *19*(3), 367–387.

Doucouliagos, C. (2016). Meta-regression analysis: Producing credible estimates from diverse evidence. *IZA World of Labor*, (November), 1–10.

Doucouliagos, C., & Stanley, T. D. (2013). Are all economic facts greatly exaggerated? Theory competition and selectivity. *Journal of Economic Surveys*, *27*(2), 316–339.

Doucouliagos, H. (2011). *How Large is Large ? Preliminary and relative guidelines for interpreting partial correlations in economics.*

Doucouliagos, H., & Stanley, T. D. (2009). Publication selection bias in minimum-wage research? A meta-regression analysis. *British Journal of Industrial Relations*, *47*(2), 406–428.

Doucouliagos, H., Stanley, T. D., & Viscusi, W. K. (2014). Publication selection and the income elasticity of the value of a statistical life. *Journal of Health Economics*, *33*(1), 67–75.

Dowd, K., & Burke, K. J. (2013). The influence of ethical values and food choice motivations on intentions to purchase sustainably sourced foods. *Appetite*, *69*, 137–144.

Dubbert, C. (2019). Participation in contract farming and farm performance: Insights from cashew farmers in Ghana. *Agricultural Economics*, *50*(6), 749–763.

Dudley, N., & Alexander, S. (2017). Agriculture and biodiversity: a review. *Biodiversity*, *18*(2-3), 45–49.

Duffy, J., Lebeau, L., & Puzzello, D. (2021). Bargaining under liquidity constraints: nash vs. kalai in the laboratory. *Kalai in the Laboratory (October 18, 2021).*

Dunlap, R. E., Van Liere, K. D., Mertig, A. G., & Jones, R. E. (2000). New trends in measuring environmental attitudes: Measuring endorsement of the new ecological paradigm: A revised NEP scale. *Journal of Social Issues*, *56*(3), 425–442.

Eicher, T. S., Papageorgiou, C., & Raftery, A. E. (2011). Default priors and predictive performance in Bayesian averaging, with application to growth determinants. *Journal of Applied Econometrics*, *26*, 30–55.

Espinosa-Goded, M., Barreiro-Hurlé, J., & Ruto, E. (2010). What do farmers want from agri-environmental scheme design? A choice experiment approach. *Journal of Agricultural economics*, *61*(2), 259–273.

Eyhorn, F., Muller, A., Reganold, J. P., Frison, E., Herren, H. R., Luttikholt, L., Mueller, A., Sanders, J., Scialabba, N. E.-H., Seufert, V., et al. (2019). Sustainability in global agriculture driven by organic farming. *Nature sustainability*, *2*(4), 253–255.

Farrow, K., Grolleau, G., & Ibanez, L. (2017). Social Norms and Pro-environmental Behavior: A Review of the Evidence. *Ecological Economics*, *140*, 1–13.

Gáfaro, M., & Mantilla, C. (2020). Land division: a lab-in-the-field bargaining experiment. *Journal of Development Economics*, *146*, 102525.

Garfield, Z. H., Syme, K. L., & Hagen, E. H. (2020). Universal and variable leadership dimensions across human societies. *Evolution and Human Behavior*, *41*(5), 397–414.

Genius, M., Pantzios, C. J., Tzouvelekas, V., et al. (2006). Information acquisition and adoption of organic farming practices. *Journal of Agricultural and Resource Economics*, *31*(1), 1–21.

Goldstein, N. J., Cialdini, R. B., & Griskevicius, V. (2008). A Room with a Viewpoint: Using Social Norms to Motivate Environmental Conservation in Hotels. *Journal of Consumer Research*, *35*(3), 472–482.

Greiner, R. (2016). Factors influencing farmers' participation in contractual biodiversity conservation: A choice experiment with northern Australian pastoralists. *Australian Journal of Agricultural and Resource Economics*, *60*(1), 1–21.

Grovermann, C., Hoi, P. V., Yen, N. T. B., Schreinemachers, P., Hai, M. N., & Ferrand, P. (2024). Impact of participatory guarantee systems on sustainability outcomes: the case of vegetable farming in vietnam. *International Journal of Agricultural Sustainability*, *22*(1), 2338028.

Guido, G., Prete, M. I., Peluso, A. M., Maloumby-Baka, R. C., & Buffa, C. (2010). The role of ethics and product personality in the intention to purchase organic food products: A structural equation modeling approach. *International Review of Economics*, *57*(1), 79–102.

Gunby, P., Jin, Y., & Robert Reed, W. (2017). Did FDI Really Cause Chinese Economic Growth? A Meta-Analysis. *World Development*, *90*, 242–255.

Gurevitch, J., Koricheva, J., Nakagawa, S., & Stewart, G. (2018). Meta-analysis and the science of research synthesis. *Nature*, *555*(7695), 175–182.

Ha, T. M., Shakur, S., & Do, K. H. P. (2019). Consumer concern about food safety in Hanoi, Vietnam. *Food Control*, *98*, 238–244.

Hall, K., & Rhoades, E. (2010). Influence of subjective norms and communication preferences on grain farmers' attitudes toward organic and non-organic farming. *Journal of Applied Communications*, *94*(3), 51–65.

Hanemann, W. M. (1984). Welfare evaluations in contingent valuation experiments with discrete responses. *American Journal of Agricultural Economics*, *66*(3), 332–341.

Hanley, N., Mourato, S., & Wright, R. E. (2001). Choice modelling approaches: A superior alternative for environmental valuation? *Journal of Economic Surveys*, *15*(3), 435–462.

Havranek, T., Horvath, R., & Zeynalov, A. (2016). Natural Resources and Economic Growth: A Meta-Analysis. *World Development*, *88*(609642), 134–151.

Havranek, T., Irsova, Z., & Zeynalova, O. (2018). Tuition Fees and University Enrolment: A Meta-Regression Analysis. *Oxford Bulletin of Economics and Statistics*, *80*(6), 1145–1184.

Henrich, J., Chudek, M., & Boyd, R. (2015). The big man mechanism: How prestige fosters cooperation and creates Prosocial leaders. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *370*(1683).

Hensher, D. A. (1982). Functional measurement, individual preference and discrete-choice modelling: Theory and application. *Journal of Economic Psychology*, *2*(4), 323–335.

Hermalin, B. E. (1998). Toward an Economic Theory of Leadership: Leading by Example. *American Economic Review*, *88*(5), 1188–1196.

Hermann, D., Mußhoff, O., & Agethen, K. (2016). Investment behavior and status quo bias of conventional and organic hog farmers: an experimental approach. *Renewable agriculture and food systems*, *31*(4), 318–329.

Hoang-Khac, L., Tiet, T., To-The, N., & Nguyen-Anh, T. (2021). Impact of human capital on technical efficiency in sustainable food crop production: a meta-analysis. *International Journal of Agricultural Sustainability*, *0*(0), 1–22.

Hoi, P. V., Mol, A. P., Oosterveer, P., van den Brink, P. J., & Huong, P. T. (2016). Pesticide use in Vietnamese vegetable production: A 10-year study. *International Journal of Agricultural Sustainability*, *14*(3), 325–338.

Hole, A. R. (2007). A comparison of approaches to estimating confidence intervals for willingness to pay measures. *Health Economics*, *16*(8), 827–840.

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American economic review*, *92*(5), 1644–1655.

Hoque, M. Z., Akhter, N., & Mawa, Z. (2021). Consumers' willingness to pay (WTP) for organically farmed fish in Bangladesh. *Journal of Agricultural and Applied Economics*, *53*(4), 482–509.

Hornik, J., Cherian, J., Madansky, M., & Narayana, C. (1995). Determinants of recycling behavior: A synthesis of research results. *Journal of Socio-Economics*, *24*(1), 105–127.

Hynes, S., Hanley, N., et al. (2005). *Analysing preference heterogeneity using random parameter logit and latent class modelling techniques*. Department of Economics, National University of Ireland, Galway.

Jackson, M. O. (2010). *Social and Economic Networks*. Princeton University Press.

Jaeck, M., & Lifran, R. (2014). Farmers' Preferences for Production Practices: A Choice Experiment Study in the Rhone River Delta. *Journal of Agricultural Economics*, *65*(1), 112–130.

Jaime, M. M., Coria, J., & Liu, X. (2016). Interactions between CAP agricultural and agri-environmental subsidies and their effects on the uptake of organic farming. *American Journal of Agricultural Economics*, *98*(4), 1114–1145.

Joshi, Y., & Rahman, Z. (2015). *Factors Affecting Green Purchase Behaviour and Future Research Directions* (Vol. 3). Holy Spirit University of Kaslik.

Jouzi, Z., Azadi, H., Taheri, F., Zarafshani, K., Gebrehiwot, K., Van Passel, S., & Lebailly, P. (2017). Organic farming and small-scale farmers: main opportunities and challenges. *Ecological economics*, *132*, 144–154.

Kalai, E. (1977). Nonsymmetric nash solutions and replications of 2-person bargaining. *International Journal of Game Theory*, *6*, 129–133.

Kallas, Z., Serra, T., & Gil, J. M. (2010). Farmers' objectives as determinants of organic farming adoption: The case of Catalonian vineyard production. *Agricultural Economics*, *41*(5), 409–423.

Khare, A. (2015). Antecedents to green buying behaviour: a study on consumers in an emerging economy. *Marketing Intelligence & Planning*, *33*(3), 309–329.

Klöckner, C. A., & Ohms, S. (2009). The importance of personal norms for purchasing organic milk. *British Food Journal*, *111*(11), 1173–1187.

Knapp, S., & van der Heijden, M. G. (2018). A global meta-analysis of yield stability in organic and conservation agriculture. *Nature communications*, *9*(1), 3632.

Kosfeld, B. M., & Rustagi, D. (2015). Leader punishment and cooperation in groups : Experimental field evidence from commons management in Ethiopia. *American Economic Review*, *105*(2), 747–783.

Krah, K., Petrolia, D. R., Williams, A., Coble, K. H., Harri, A., & Rejesus, R. M. (2018). Producer preferences for contracts on a risky bioenergy crop. *Applied Economic Perspectives and Policy*, *40*(2), 240–258.

Krishnan, P., & Patnam, M. (2014). Neighbors and extension agents in ethiopia: who matters more for technology adoption? *American Journal of Agricultural Economics*, *96*(1), 308–327.

Kuminoff, N. V., & Wossink, A. (2010). Why isn't more us farmland organic? *Journal of Agricultural Economics*, *61*(2), 240–258.

Kwanmuang, K., Wangyeesen, A., & Shuto, H. (2018). What Leads Farmers to Abandon Coffee Production?: An Experimental Study on Crop Choice in Chumphon Province, Thailand. *Japanese Journal of Agricultural Economics*, *20*(0), 18–37.

Lakitan, B. (2019). Research and technology development in Southeast Asian economies are drifting away from agriculture and farmers' needs. *Journal of Science and Technology Policy Management*, *10*(1), 251–272.

Läpple, D., & Kelley, H. (2013). Understanding the uptake of organic farming: Accounting for heterogeneities among Irish farmers. *Ecological Economics*, *88*, 11–19.

Läpple, D., & Kelley, H. (2015). Spatial dependence in the adoption of organic drystock farming in Ireland. *European Review of Agricultural Economics*, *42*(2), 315–337.

Läpple, D., & Van Rensburg, T. (2011). Adoption of organic farming: Are there differences between early and late adoption? *Ecological Economics*, *70*(7), 1406–1414.

Lazaric, N., Le Guel, F., Belin, J., Oltra, V., Lavaud, S., & Douai, A. (2019). Determinants of sustainable consumption in France: The importance of social influence and environmental values. *Journal of Evolutionary Economics*, *0*(0), 1–30.

Liang, R.-d. (2016). Predicting intentions to purchase organic food: The moderating effects of organic food prices. *British Food Journal*, *118*(1), 183–199.

Liu, H., Meng, J., Bo, W., Cheng, D., Li, Y., Guo, L., Li, C., Zheng, Y., Liu, M., Ning, T., et al. (2016). Biodiversity management of organic farming enhances agricultural sustainability. *Scientific Reports*, *6*(1), 1–8.

Lodorfos, G. N., & Dennis, J. (2008). Consumers' intent: In the organic food market. *Journal of Food Products Marketing*, *14*(2), 17–38.

Lotter, D. W. (2003). Organic agriculture. *Journal of Sustainable Agriculture*, *21*(4), 59–128.

Luhan, W. J., Poulsen, O., & Roos, M. W. (2019). Money or morality: fairness ideals in unstructured bargaining. *Social Choice and Welfare*, *53*, 655–675.

Maertens, A. (2017). Who cares what others think (or do)? Social learning and social pressures in cotton farming in India. *American Journal of Agricultural Economics*, *99*(4), 988–1007.

Massey, M., O'Cass, A., & Otahal, P. (2018). A meta-analytic study of the factors driving the purchase of organic food. *Appetite*, *125*, 418–427.

Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P. R., Pirani, A., Moufouma-Okia, W., Péan, C., Pidcock, R., et al. (2018). An IPCC special report on the impacts of global warming.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. *Frontiers in Econometrics*, *10*, 105–142.

Meemken, E., & Qaim, M. (2018). Organic Agriculture, Food Security, and the Environment. *Annual Review of Resource Economics*, *10*, 39–63.

Messer, K. D., Costanigro, M., & Kaiser, H. M. (2017). Labeling food processes: The good, the bad and the ugly. *Applied Economic Perspectives and Policy*, *39*(3), 407–427.

Mie, A., Andersen, H. R., Gunnarsson, S., Kahl, J., Kesse-Guyot, E., Rembiałkowska, E., Quaglio, G., & Grandjean, P. (2017). Human health implications of organic food and organic agriculture: A comprehensive review. *Environmental Health: A Global Access Science Source*, *16*(1), 1–22.

Milgroom, J., Soriano, M. A., Garrido, J. M., Gómez, J. A., & Fereres, E. (2007). The influence of a shift from conventional to organic olive farming on soil management and erosion risk in southern Spain. *Renewable Agriculture and Food Systems*, *22*(1), 1–10.

Minot, N. (2006). *Income Diversification and Poverty in the Northern Uplands of Vietnam* (Vol. 145). International Food Policy Research Institute.

Mishra, A. K., Kumar, A., Joshi, P. K., & D'Souza, A. (2018). Production risks, risk preference and contract farming: Impact on food security in India. *Applied Economic Perspectives and Policy*, *40*(3), 353–378.

Mishra, A. K., Kumar, A., Joshi, P. K., D'Souza, A., & Tripathi, G. (2018). How can organic rice be a boon to smallholders? Evidence from contract farming in India. *Food Policy*, *75*, 147–157.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., Altman, D., Antes, G., Atkins, D., Barbour, V., Barrowman, N., Berlin, J. A., Clark, J., Clarke, M., Cook, D., D'Amico, R., Deeks, J. J., Devereaux, P. J., Dickersin, K., Egger, M., Ernst, E., . . . Tugwell, P. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine*, *6*(7).

Mosier, S. L. (2017). *Creating organic standards in us states: the diffusion of state organic food and agriculture legislation, 1976–2010*. Lexington Books.

Muller, A., Schader, C., El-Hage Scialabba, N., Brüggemann, J., Isensee, A., Erb, K.-H., Smith, P., Klocke, P., Leiber, F., Stolze, M., et al. (2017). Strategies for feeding the world more sustainably with organic agriculture. *Nature communications*, *8*(1), 1–13.

Murphy, R. O., & Ackermann, K. A. (2014). Social value orientation: theoretical and measurement issues in the study of social preferences. *Personality and Social Psychology Review*, *18*(1), 13–41.

Murphy, R. O., Ackermann, K. A., & Handgraaf, M. J. (2011). Measuring social value orientation. *Judgment and Decision making*, *6*(8), 771–781.

My, K. B., Nguyen-Van, P., Pham, T. K. C., Stenger, A., Tiet, T., & To-The, N. (2022). Drivers of organic farming: lab-in-the-field evidence of the role of social comparison and information nudge in networks in vietnam. *Ecological Economics*, *196*, 107401.

My, N. H., Rutsaert, P., Van Loo, E. J., Verbeke, W., Nguyen, M. H., Rutsaert, P., Van Loo, E. J., & Verbeke, W. (2017). Consumers' familiarity with and attitudes towards food quality certifications for rice and vegetables in Vietnam. *Food Control*, *82*, 74–82.

Myerson, R. B. (1984). Two-person bargaining problems with incomplete information. *Econometrica: Journal of the Econometric Society*, 461–487.

Mzoughi, N. (2011). Farmers adoption of integrated crop protection and organic farming: Do moral and social concerns matter? *Ecological Economics*, *70*(8), 1536–1545.

Namuwoza, C., & Tushemerirwe, H. (2011). Uganda: country report. In *The World of Organic Agriculture - Statistics and Emerging Trends 2011*. The World of Organic Agriculture.

Nash, J. (1953). Two-person cooperative games. *Econometrica: Journal of the Econometric Society*, 128–140.

Nguyen, C. T., Vo, T. T., Nguyen, T. X., Nguyen, H. P., Bui, D. D., Nguyen, V. M., & Duong, V. H. (2022). Assessment of pesticide residues in organic rice production in the mekong delta, vietnam. *European Journal of Development Studies*, *2*(3), 1–11.

Nguyen-Anh, T., Hoang-Duc, C., Tiet, T., Nguyen-Van, P., & To-The, N. (2022). Composite effects of human, natural and social capitals on sustainable food-crop farming in sub-saharan africa. *Food Policy*, *0*(0), 102284.

Nguyen-Van, P., Stenger, A., & Tiet, T. (2021). Social incentive factors in interventions promoting sustainable behaviors: a meta-analysis. *PloS One*, *16*(12), e0260932.

Norton, G. W., & Alwang, J. (2020). Changes in agricultural extension and implications for farmer adoption of new practices. *Applied Economic Perspectives and Policy*, *42*(1), 8–20.

Nyblom, J., Borgatti, S., Roslakka, J., & Salo, M. A. (2003). Statistical analysis of network data - an application to diffusion of innovation. *Social Networks*, *25*(2), 175–195.

Olli, E., Grendstad, G., & Wollebaek, D. (2001). Correlates of environmental behaviors: Bringing back social context. *Environment and Behavior*, *33*(2), 181–208.

Organization, W. H. (2001). *Codex alimentarius: organically produced foods*. Food; Agriculture Organization of the United Nations (FAO).

Padel, S. (2001). Conversion to organic farming: A typical example of the diffusion of an innovation? (Special issue: Politics, ideology and practice of organic farming). *Sociologia Ruralis*, *41*(1), 40–61.

Papke, L. E., & Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of applied econometrics*, *11*(6), 619–632.

Papke, L. E., & Wooldridge, J. M. (2008). Panel data methods for fractional response variables with an application to test pass rates. *Journal of econometrics*, *145*(1-2), 121–133.

Park, T. A., & Lohr, L. (2007). Meeting the needs of organic farmers: Benchmarking organizational performance of university extension. *Applied Economic Perspectives and Policy*, *29*(1), 141–155.

Peterson, H. H., Barkley, A., Chacon-Cascante, A., & Kastens, T. L. (2012). The motivation for organic grain farming in the United States: profits, lifestyle, or the environment? *Journal of Agricultural and Applied Economics*, *44*(2), 137–155.

Pham, H.-G., Chuah, S.-H., & Feeny, S. (2021). Factors affecting the adoption of sustainable agricultural practices: findings from panel data for vietnam. *Ecological Economics*, *184*, 107000.

Pham, V. H., Mol, A. P., & Oosterveer, P. J. (2009). Market governance for safe food in developing countries: The case of low-pesticide vegetables in Vietnam. *Journal of Environmental Management*, *91*(2), 380–388.

Pielstick, C. D. (2000). Formal vs. informal leading: A comparative analysis. *Journal of Leadership Studies*, *7*(3), 99–114.

Pietraszewski, D. (2020). The evolution of leadership: leadership and followership as a solution to the problem of creating and executing successful coordination and cooperation enterprises. *The Leadership Quarterly*, *31*(2), 101299.

Pilarova, T., Bavorova, M., & Kandakov, A. (2018). Do farmer, household and farm characteristics influence the adoption of sustainable practices? The evidence from the Republic of Moldova. *International Journal of Agricultural Sustainability*, *16*(4-5), 367–384.

Pimentel, D., & Burgess, M. (2014). An environmental, energetic and economic comparison of organic and conventional farming systems. *Integrated Pest Management: Pesticide Problems, Vol. 3*, 141–166.

Potters, J., Sefton, M., & Vesterlund, L. (2005). After you - Endogenous sequencing in voluntary contribution games. *Journal of Public Economics*, *89*(8 SPEC. ISS.), 1399–1419.

Potters, J., Sefton, M., & Vesterlund, L. (2007). Leading-by-example and signaling in voluntary contribution games: An experimental study. *Economic Theory*, *33*(1), 169–182.

Povey, R., Conner, M., Sparks, P., James, R., & Shepherd, R. (2000). The theory of planned behaviour and healthy eating: Examining additive and moderating effects of social influence variables. *Psychology and Health*, *14*(6), 991–1006.

Ramalho, J. J. S. (2019). Modeling fractional responses using r. In *Handbook of statistics* (pp. 245–279, Vol. 41). Elsevier.

Ramankutty, N., Ricciardi, V., Mehrabi, Z., & Seufert, V. (2019). Trade-offs in the performance of alternative farming systems. *Agricultural Economics (United Kingdom)*, *50*(S1), 97–105.

Rapsomanikis, G. (2015). An analysis based on household surveys. In *The economic lives of smallholder farmers*. Food; Agriculture Organization of the United Nations, Rome, Italy.

Reganold, J. P., & Wachter, J. M. (2016). Organic agriculture in the twenty-first century. *Nature plants*, *2*(2), 1–8.

Richter, C. H., Custer, B., Steele, J. A., Wilcox, B. A., & Xu, J. (2015). Intensified food production and correlated risks to human health in the Greater Mekong Subregion: A systematic review. *Environmental Health: A Global Access Science Source*, *14*(1), 1–13.

Robinson, E., Thomas, J., Aveyard, P., & Higgs, S. (2014). What everyone else is eating: A systematic review and meta-analysis of the effect of informational eating norms on eating behavior. *Journal of the Academy of Nutrition and Dietetics*, *114*(3), 414–429.

Rosina Bara, C., Jarquin Gálvez, R., Reyes Hernández, H., & Fortanelli Martínez, J. (2018). Adaptation of a participatory organic certification system to the organic products law in six local markets in Mexico. *Agroecology and Sustainable Food Systems*, *42*(1), 48–76.

Roth, A. E., Malouf, M. W., & Murnighan, J. K. (1981). Sociological versus strategic factors in bargaining. *Journal of Economic Behavior & Organization*, *2*(2), 153–177.

Roth, A. E., & Murnighan, J. K. (1982). The role of information in bargaining: an experimental study. *Econometrica: Journal of the Econometric Society*, 1123–1142.

Roth, A. E., & Rothblum, U. G. (1982). Risk aversion and nash's solution for bargaining games with risky outcomes. *Econometrica: Journal of the Econometric Society*, 639–647.

Rubinstein, A. (1982). Perfect equilibrium in a bargaining model. *Econometrica: Journal of the Econometric Society*, 97–109.

Rubinstein, A. (1985). A bargaining model with incomplete information about time preferences. *Econometrica: Journal of the Econometric Society*, 1151–1172.

Ruml, A., & Qaim, M. (2021). New evidence regarding the effects of contract farming on agricultural labor use. *Agricultural Economics*, *52*(1), 51–66.

Sapbamrer, R., & Thammachai, A. (2021). A systematic review of factors influencing farmers' adoption of organic farming. *Sustainability*, *13*(7), 1–28.

Scalco, A., Noventa, S., Sartori, R., & Ceschi, A. (2017). Predicting organic food consumption: A meta-analytic structural equation model based on the theory of planned behavior. *Appetite*, *112*, 235–248.

Scarpa, R., Zanoli, R., Bruschi, V., & Naspetti, S. (2013). Inferred and stated attribute non-attendance in food choice experiments. *American Journal of Agricultural Economics*, *95*(1), 165–180.

Schneeberger, W., Darnhofer, I., & Eder, M. (2002). Barriers to the adoption of organic farming by cash-crop producers in Austria. *American Journal of Alternative Agriculture*, *17*(1), 24–31.

Schneider, M. K., Lüscher, G., Jeanneret, P., Arndorfer, M., Ammari, Y., Bailey, D., Balázs, K., Báldi, A., Choisis, J. P., Dennis, P., Eiter, S., Fjellstad, W., Fraser, M. D., Frank, T., Friedel, J. K., Garchi, S., Geijzendorffer, I. R., Gomiero, T., Gonzalez-Bornay, G., … Herzog, F. (2014). Gains to species diversity in organically farmed fields are not propagated at the farm level. *Nature Communications*, *5*(May), 1–9.

Schultz, P. W. (2001). The structure of environmental concern: concern for self, other people, and the biosphere. *Journal of environmental psychology*, *21*(4), 327–339.

Schulz, N., Breustedt, G., & Latacz-Lohmann, U. (2014). Assessing farmers' willingness to accept "greening": Insights from a discrete choice experiment in Germany. *Journal of Agricultural Economics*, *65*(1), 26–48.

Seufert, V., Ramankutty, N., & Foley, J. A. (2012). Comparing the yields of organic and conventional agriculture. *Nature*, *485*(7397), 229–232.

Seufert, V., Ramankutty, N., & Mayerhofer, T. (2017). What is this thing called organic? – How organic farming is codified in regulations. *Food Policy*, *68*, 10–20.

Shennan, C., Krupnik, T. J., Baird, G., Cohen, H., Forbush, K., Lovell, R. J., & Olimpi, E. M. (2017). Organic and conventional agriculture: a useful framing? *Annual Review of Environment and Resources*, *42*, 317–346.

Shimokawa, S., Hu, D., Li, D., & Cheng, H. (2021). The urban–rural gap in the demand for food safety in China: The role of food label knowledge. *Agricultural Economics*, *52*(2), 175–193.

Sleeth-Keppler, D., Perkowitz, R., & Speiser, M. (2017). It's a matter of trust: american judgments of the credibility of informal communicators on solutions to climate change. *Environmental Communication*, *11*(1), 17–40.

Sligo, F., & Massey, C. (2007). Risk, trust and knowledge networks in farmers' learning. *Journal of Rural Studies*, *23*(2), 170–182.

Soltani, S., Azadi, H., Mahmoudi, H., & Witlox, F. (2014). Organic agriculture in Iran: Farmers' barriers to and factors influencing adoption. *Renewable Agriculture and Food Systems*, *29*(2), 126–134.

Spence, M., Stancu, V., Elliott, C., Dean, M., et al. (2018). Exploring consumer purchase intentions towards traceable minced beef and beef steak using the theory of planned behavior. *Food Control*, *91*, 138–147.

Stanley, T. D. (2005). Beyond Publication Bias. *Journal of Economic Surveys*, *19*(3), 309–345.

Stanley, T. D., Doucouliagos, C., & Jarrell, S. B. (2008). Meta-regression analysis as the socio-economics of economics research. *Journal of Socio-Economics*, *37*(1), 276–292.

Stanley, T. D., & Doucouliagos, H. (2014). Meta-regression approximations to reduce publication selection bias. *Research Synthesis Methods*, *5*(1), 60–78.

Stanley, T. D., Doucouliagos, H., & Steel, P. (2018). Does Ict Generate Economic Growth? a Meta-Regression Analysis. *Journal of Economic Surveys*, *32*(3), 705–726.

Stanley and Doucouliagos, H., T. D. (2012). *Meta-Regression Analysis in Economics and Business.*

Stolze, M., & Lampkin, N. (2009). Policy for organic farming: rationale and concepts. *Food Policy*, *34*(3), 237–244.

Sumberg, J., & Giller, K. E. (2022). What is 'conventional'agriculture? *Global Food Security*, *32*, 100617.

Takahashi, K., Mano, Y., & Otsuka, K. (2019). Learning from experts and peer farmers about rice production: experimental evidence from cote d'ivoire. *World Development*, *122*, 157–169.

Tarkiainen, A., & Sundqvist, S. (2005). Subjective norms, attitudes and intentions of Finnish consumers in buying organic food. *British Food Journal*, *107*(11), 808–822.

Testa, F., Sarti, S., & Frey, M. (2019). Are green consumers really green? Exploring the factors behind the actual consumption of organic food products. *Business Strategy and the Environment*, *28*(2), 327–338.

Thai, N. T., Manh, H. T., & Pensupar, K. (2017). Consumers' preferences and willingness to pay for VietGAP vegetables in Hanoi, Vietnam. *International Journal of Economic Research*, *14*(16), 401–419.

Tiet, T., Nguyen-Anh, T., et al. (2022). Farmers' behaviors and attitudes toward climate change adaptation: evidence from Vietnamese smallholder farmers. *Environment, Development and Sustainability*, *0*, 1–26.

Tiet, T., Nguyen-Van, P., Pham, T. K. C., Stenger, A., Boun My, K., & Nguyen, H. (2021). Farmers' preferences towards organic farming: evidence from a discrete choice experiment in northern vietnam.

Tilman, D., Cassman, K. G., Matson, P. A., Naylor, R., & Polasky, S. (2002). Agricultural sustainability and intensive production practices. *Nature*, *418*(6898), 671–677.

Tilman, D., & Clark, M. (2015). Food, agriculture & the environment: Can we feed the world & save the earth? *Daedalus*, *144*(4), 8–23.

Toan, P. V., Sebesvari, Z., Bläsing, M., Rosendahl, I., & Renaud, F. G. (2013). Pesticide management and their residues in sediments and surface and drinking water in the Mekong Delta, Vietnam. *Science of the Total Environment*, *452*, 28–39.

Tran, D., Broeckhoven, I., Hung, Y., Diem My, N. H., De Steur, H., & Verbeke, W. (2022). Willingness to pay for food labelling schemes in Vietnam: A choice experiment on Water Spinach. *Foods*, *11*(5), 722.

Tran-Nam, Q., & Tiet, T. (2022). The role of peer influence and norms in organic farming adoption: accounting for farmers' heterogeneity. *Journal of Environmental Management*, *320*, 115909.

Tuomisto, H. L., Hodge, I. D., Riordan, P., & Macdonald, D. W. (2012). Does organic farming reduce environmental impacts?–a meta-analysis of european research. *Journal of environmental management*, *112*, 309–320.

Uematsu, H., & Mishra, A. K. (2012). Organic farmers or conventional farmers: where's the money? *Ecological Economics*, *78*, 55–62.

Unay Gailhard, İ., Bavorová, M., & Pirscher, F. (2015). Adoption of agri-environmental measures by organic farmers: The role of interpersonal communication. *The Journal of Agricultural Education and Extension*, *21*(2), 127–148.

Unnevehr, L. J. (2022). Addressing food safety challenges in rapidly developing food systems. *Agricultural Economics*, *53*(4), 529–539.

Van Campenhout, B., Spielman, D. J., & Lecoutere, E. (2020). Information and communication technologies to provide agricultural advice to smallholder farmers: experimental evidence from uganda. *American Journal of Agricultural Economics*, *00*(0), 1–21.

Van den Broeck, G., Vlaeminck, P., Raymaekers, K., Vande Velde, K., Vranken, L., & Maertens, M. (2017). Rice farmers' preferences for fairtrade contracting in Benin: Evidence from a discrete choice experiment. *Journal of Cleaner Production*, *165*, 846–854.

Van Dijk, E., De Cremer, D., & Handgraaf, M. J. (2004). Social value orientations and the strategic use of fairness in ultimatum bargaining. *Journal of experimental social psychology*, *40*(6), 697–707.

Van Hoi, P., Mol, A., & Oosterveer, P. (2013). State governance of pesticide use and trade in Vietnam. *NJAS - Wageningen Journal of Life Sciences*, *67*, 19–26.

Van Hoi, P., Mol, A. P., & Oosterveer, P. J. (2009). Market governance for safe food in developing countries: The case of low-pesticide vegetables in Vietnam. *Journal of Environmental Management*, *91*(2), 380–388.

Vesterlund, L. (2003). The informational value of sequential fundraising. *Journal of Public Economics*, *87*(3-4), 627–657.

Vietnamese Goverment. (2020). *Project for the development of organic agriculture phase 2020-2030*. Retrieved May 3, 2024, from https://vanban.chinhphu.vn/default.aspx?pageid=27160&docid=200315

Villanueva, A. J., Gómez-Limón, J. A., Arriaza, M., & Rodríguez-Entrena, M. (2015). The design of agri-environmental schemes: Farmers' preferences in Southern Spain. *Land Use Policy*, *46*, 142–154.

Von Neumann, J., & Morgenstern, O. (2007). Theory of games and economic behavior. In *Theory of games and economic behavior*. Princeton university press.

Vu, H. T., Tran, D., Goto, D., & Kawata, K. (2020). Does experience sharing affect farmers' pro-environmental behavior? a randomized controlled trial in vietnam. *World Development*, *136*, 105062.

Weiss, J., & Khan, H. (2006). *Poverty strategies in asia: a growth plus approach*. Edward Elgar Publishing.

Willer, H., & Lernoud, J. (2019). *The world of organic agriculture. statistics and emerging trends 2019*. Research Institute of Organic Agriculture FiBL; IFOAM Organics International.

Willer, H., Trávniček, J., & Schlatter, S. (2024). *The world of organic agriculture. statistics and emerging trends 2024*. Research Institute of Organic Agriculture FiBL; IFOAM-Organics International.

Wittwer, R. A., Bender, S. F., Hartman, K., Hydbom, S., Lima, R. A., Loaiza, V., Nemecek, T., Oehl, F., Olsson, P. A., Petchey, O., et al. (2021). Organic and conservation agriculture promote ecosystem multifunctionality. *Science Advances*, *7*(34), eabg6995.

Wollni, M., & Andersson, C. (2014). Spatial patterns of organic agriculture adoption: Evidence from Honduras. *Ecological Economics*, *97*, 120–128.

World Bank. (2016). *Vietnam food safety risks management: Challenges and opportunities* (tech. rep.). World Bank. Hanoi.

Wu, L., Xu, L., & Gao, J. (2011). The acceptability of certified traceable food among Chinese consumers. *British Food Journal*, *113*(4), 519–534.

Youngberg, G., & DeMuth, S. P. (2013). Organic agriculture in the United States: A 30-year retrospective. *Renewable Agriculture and Food Systems*, *28*(4), 294–328.

Zabel, F., Delzeit, R., Schneider, J. M., Seppelt, R., Mauser, W., & Vaclavik, T. (2019). Global impacts of future cropland expansion and intensification on agricultural markets and biodiversity. *Nature communications*, *10*(1), 2844.

Zeng, Y., Tian, Y., He, K., & Zhang, J. (2019). Environmental conscience, external incentives and social norms in rice farmers' adoption of pro-environmental agricultural practices in rural Hubei province, China. *Environmental Technology*, *3330*, 1–40.

Zeugner, S., & Feldkircher, M. (2015). Bayesian model averaging employing fixed and flexible priors: The BMS package for R. *Journal of Statistical Software*, *68*(4).

Zhengfei, G., Lansink, A. O., Wossink, A., & Huirne, R. (2005). Damage control inputs: a comparison of conventional and organic farming systems. *European Review of Agricultural Economics*, *32*(2), 167–189.