

# Transformation towards a more sustainable agricultural system in Indonesia: Empirical essays on the role of information and endorsement

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# Abstract

Agricultural intensification has led to rapid increases in productivity and thereby brought massive reductions in poverty. Yet, the agricultural sector is also a major contributor to many of today's environmental challenges. Agrochemical pollution, unsustainable nutrition management and land burning cause biodiversity loss and land degradation, and directly contribute to climate change. However, agriculture is not only a major contributor but also a victim. A transition towards more sustainable agricultural systems is crucial to secure the needs of current and future generations. Given that more than 70 percent of the world's poor rely on natural resources for their livelihood, biodiversity loss, land degradation and climate change will disproportionately affect those who are least able to compensate for the losses. Increased international awareness of the challenges associated with current agricultural systems is strongly reflected in the United Nations Sustainable Development Goals.

In many cases, transitioning towards sustainable agricultural production requires farmers to change their practices. These changes can include the adoption of sustainable agricultural practices, water-saving, or the disadoption of excessive chemical input use or land burning. Policy makers interested in making agricultural production more sustainable need to understand what encourages the uptake of sustainable practices and what is effective in reducing unsustainable practices. This thesis seeks to understand whether and how information provision and endorsement can contribute to the transition towards more sustainable agricultural systems.

In the context of Indonesia, this thesis investigates pathways to more sustainable production systems focussing on agricultural land burning, organic farming and organic consumption. The current Indonesian agricultural system has severe negative environmental impacts, locally and globally, and a transformation leading to a more environmentally sustainable system is needed. High levels of deforestation, for example, threaten the country's biodiversity, reduce soil organic content and are part of the reason why Indonesia is one of the largest greenhouse gas emitters globally. Despite some contradictory policies, and challenges in the enforcement of existing regulations, the government shows commitment to addressing the negative impacts of agricultural production on the environment. This thesis aims to inform policies promoting this transition towards a more sustainable agricultural production system.

Specifically, this thesis addresses the following three questions in three self-contained papers: Firstly, can faith-based endorsement by a religious institution encourage the disadoption of unsustainable practices? Secondly, can hands-on training encourage the adoption of sustainable practices? Thirdly, is there local demand for certified organic food and can information increase the potential premium consumers are willing to pay?

The first paper explores the potential of religious endorsement for inducing pro-environmental behaviour and encouraging the disadoption of fire as an agricultural practice, thereby preventing forest fires. Forest fires are increasing in both frequency and intensity in many tropical countries. Forest fires are detrimental to the environment and human welfare, thus it is vital to better understand how they can be prevented. Most of these fires are caused by human activities, such as land clearing. The paper analyses the impact of a fatwa (an Islamic religious ruling) on reducing fire incidence in Indonesia. The fatwa states that the burning of forests and land is forbidden and was issued by an important Indonesian Islamic organisation following the latest extreme fire season in 2015. To analyse the impact of the fatwa, I employ a difference-in-difference approach with a matched sample and compare fire incidence in Muslim majority and non-Muslim majority villages before and after the fatwa was issued. I use an eight-year panel dataset that spans around 29,300 rural villages and combines village census data with remote sensing data of fires. Results indicate that fire incidence decreased in Muslim majority villages following the issuing of the fatwa. For the post-fatwa period from August 2016 to December 2019, the average monthly effect amounts to around 2.2 prevented fire events per village. This is a considerable effect. The paper concludes that fire prevention efforts, and potentially other environmental conservation efforts, could benefit significantly from support by religious institutions and stakeholders.

The second paper, co-authored with Michael Grimm, investigates the role of information provision and training for the adoption of organic farming practices in Java, Indonesia. Previous studies highlighted information as an important driver of agricultural technology adoption. Yet, little is known about the effect of removing information constraints in the context of organic farming. We use a randomised controlled trial (RCT) to identify the impact of a three-day hands-on training in organic farming for smallholder farmers. We find that the training intervention increased the adoption of organic inputs and had a positive and statistically significant effect on farmers' knowledge and perceptions of organic farming. Overall, our findings suggest that information constraints are a barrier to the adoption of organic farming, as information provision increased the use of organic

farming practices. Endorsement may have additionally contributed to the impact of the training, as encouragement to use organic farming practices by an external trainer may have acted as a form of ‘expert validation’. Interestingly, we find that farmers were motivated not only by the price premium that is associated with organic products but also by the prospect of improved soil quality that is associated with organic farming practices. However, as expected, we cannot yet observe complete conversion to organic farming by farmers in the treatment group; rather it seems that a sizeable share of farmers in the treatment group has started to experiment with methods taught in the training while simultaneously continuing to use chemical inputs.

The third paper, co-authored with Michael Grimm and Franziska Steinhübel, investigates whether urban and suburban Indonesian consumers are willing to pay a price premium for organic food. Sufficient local demand is an essential requirement for further adoption of organic farming by smallholders, who typically have limited access to export markets. Until now only few studies have explored local willingness to pay (WTP) for organic products in low- and middle-income countries using a non-hypothetical experiment. We use an incentive-compatible auction based on the Becker-DeGroot-Marschak (BDM) approach to elicit consumers’ WTP. We further study the effect of income and a randomised information treatment about the benefits of organic food on respondents’ WTP. Estimates suggest that consumers are willing to pay a price premium for organic rice, on average 20 percent more than what they paid for conventional rice outside of our experiment. However, our results also indicate that raising consumers’ WTP further is complex. Showing participants a video about the health or, alternatively, environmental benefits of organic food was not effective in further raising WTP. Exposure to the environmental benefits video was, however, effective in raising stated organic food consumption intentions. The results can be used as a basis for the design of alternative awareness measures to increase knowledge, interest and demand for organic food.

Together, the three papers in this thesis contribute to an understanding of possible pathways towards a more sustainable agricultural system in Indonesia, and potentially also in other regions of the world.



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# List of Abbreviations

<b>AOI</b>	Aliansi Organisme Indonesia
<b>ARC</b>	Alliance of Religions and Conservation
<b>BDM</b>	Becker-DeGroot-Marschak
<b>BRG</b>	Peat Restoration Agency (Ind., 'Badan Restorasi Gambut' )
<b>CA</b>	Conservation Agriculture
<b>DiD</b>	Difference-in-Differences
<b>FDR</b>	False Discovery Rate
<b>FFS</b>	Farmer Field Schools
<b>IPM</b>	Integrated Pest Management
<b>ISFM</b>	Integrated Soil Fertility Management
<b>ITT</b>	Intention-to-Treat
<b>LATE</b>	Local Average Treatment Effect
<b>Modis</b>	Moderate Resolution Imaging Spectroradiometer
<b>MUI</b>	Indonesian Council of Ulama (Ind., 'Majelis Ulama Indonesia' )
<b>NGO</b>	Non-Governmental Organization
<b>NU</b>	Nahdlatul Ulama
<b>OLS</b>	Ordinary Least Squares
<b>PES</b>	Payments for Ecosystem Services

## LIST OF ABBREVIATIONS

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<b>PODES</b>	Village Potential Statistics (Ind., 'Potensi Desa' )
<b>RAN-GRK</b>	National Action Plan for GHG Emission Reduction (Ind., 'Rencana Aksi Nasional Penurunan Emisi Gas Rumah Kaca' )
<b>RCT</b>	Randomised Controlled Trial
<b>REDD+</b>	Reducing Emissions from Deforestation and forest Degradation
<b>RSPO</b>	Roundtable on Sustainable Palm Oil
<b>SGDs</b>	Sustainable Development Goals
<b>TRMM</b>	Tropical Rainfall Measuring Mission
<b>UN</b>	United Nations
<b>UNFCCC</b>	United Nations Framework Convention on Climate Change
<b>US</b>	United States
<b>US</b>	United States
<b>WTP</b>	Willingness to Pay
<b>Viirs</b>	Visible Infrared Imaging Radiometer Suite





# 1 Introduction

Agricultural intensification has led to rapid increases in productivity and thereby brought massive reductions in poverty. Yet, the agricultural sector is also a major contributor to many of today's environmental challenges. Agrochemical pollution, practices such as land burning, land-use change and large-scale monoculture put a strain on animal and plant life, especially insects and micro-organisms (FAO, 2019; IFAD, 2013). Poor management practices have resulted in large-scale land degradation, for example in the form of acidification, salinisation or erosion (FAO & ITPS, 2015; Kopittke, Menzies, Wang, McKenna, & Lombi, 2019). Today, the majority of global soils is in only fair or poor condition (FAO & ITPS, 2015). Furthermore, land burning and associated forest and landscape fires as well as the reduction of soil carbon levels through unsustainable nutrition management are direct contributors to climate change (Edwards, Tobias, Sheil, Meijaard, & Laurance, 2014; FAO, 2019).

However, agriculture is not only a major contributor to, but also a victim of biodiversity loss, land degradation and climate change. It depends on biodiversity and soils for ecosystem services such as pollination, natural pest control and nutrient and water supply for plants (Dominati, Mackay, Green, & Patterson, 2014; IFAD, 2013). A transition towards more sustainable agricultural systems is crucial to secure the needs of current and future generations. Given that more than 70 percent of the world's poor rely on natural resources for their livelihood, biodiversity loss, land degradation and climate change will disproportionately affect those who are least able to compensate for the losses (Ekins, Gupta, & Boileau, 2019; Nkonya, Mirzabaev, & von Braun, 2016).

Increased international awareness of the challenges associated with current agricultural systems is strongly reflected in the United Nations Sustainable Development Goals (SDGs). It is, for example, reflected directly in Goal 2 *Zero hunger: End hunger, achieve food security and improved nutrition and promote sustainable agriculture*; Goal 6 *Clean water and sanitation: Ensure availability and sustainable management of water and sanitation for all*; and Goal 15 *Life on land: Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification and halt and reverse land degradation and halt biodiversity loss*.

Yet, while there is agreement that agricultural systems urgently need to become more sustainable, the appropriate way to achieve this continues to be debated. Consequently, it is important to better understand how to promote sustainable agriculture and related pro-environmental behaviour.

This thesis seeks to understand whether and how information provision, awareness raising and endorsement can contribute to the transition towards more sustainable agricultural systems. It further investigates local demand for organic food products, which can be an important incentive for farmers to switch to sustainable farming. This thesis thereby contributes to a better understanding of how to promote more sustainable agricultural production and provides insights into what policy options could support this transformation.

### **1.1 Context: Indonesian Agricultural Sector**

The three papers contained in this thesis all deal with the transformation of the Indonesian agricultural system, but focus on different aspects, namely agricultural land burning, organic farming and organic consumption. This section provides a wider context for these papers by providing background information on the Indonesian agricultural sector.

Indonesia has a population of around 260 million and is the largest economy in South East Asia. It has the third largest area of tropical rainforest globally and a regionally diverse agricultural sector which is the main source of employment for around half of the country's rural labour force (BPS, 2018; FAO, 2017; Fitzherbert et al., 2008). Smallholders cultivating less than one hectare manage the majority of agricultural land, while large, company-run plantations manage around 15 percent of agricultural land (FAO, 2017).

Within Indonesia, the research presented in this thesis focuses on the two large and mostly forested islands Kalimantan and Sumatra (paper 1) and on Java (papers 2 and 3). Agricultural production in Kalimantan is dominated by the plantation crops palm oil and rubber; in Sumatra, coffee, cacao and rice also play an important role. Except for palm oil, the principal mode of production is small-scale farming. While company-owned plantations still produce the largest share, smallholders also increasingly contribute to the production of palm oil (Euler, Krishna, Schwarze, Siregar, & Qaim, 2017). Studies show that this adoption of palm oil by smallholders has led to increased income (Euler et al., 2017; Krishna, Euler, Siregar, & Qaim, 2017). In Java, the most densely populated Indonesian island, most agricultural households cultivate less than half a hectare (BPS, 2018). Rice remains the most important food crop with 50 percent of agricultural households planting it at least once a year (BPS, 2018).

Since the early years of the Suharto government, policy makers in Indonesia have taken an active role in agricultural development (Simatupang & Timmer, 2008). In the 1960s, the Suharto government started to roll out so-called green revolution technologies to modernise the agricultural sector in order to achieve food security and socio-economic stability (Welker, 2012). In the course of the highly centralised roll-out, the government expanded agricultural extension to equip farmers with inputs and extended and rehabilitated irrigation systems (Davidson, 2018; Thorburn, 2014). In 1979, the government initiated the formation of farmer groups within villages to facilitate the distribution of inputs and extensions (Ibnu, Offermans, & Glasbergen, 2018). Today, farmer groups remain important for the communication between the government and farmers and subsidised inputs are still largely distributed through farmer groups (Indonesian Ministry of Agriculture, 2021). Following the end of the Suharto regime and the subsequent decentralisation in the early 2000s, responsibility for many types of agricultural development and services shifted to the local level.

The green revolution and the associated agricultural intensification have contributed to income growth and welfare for a substantial share of the population. Yet, despite the successes in the last decades, the agricultural sector remains linked to poverty. Furthermore, agricultural intensification and measures undertaken to ensure food security have had negative environmental consequences. In the 1980s, pesticide-induced biodiversity loss caused a severe planthopper plague. Excessive use of pesticides had destroyed not only planthoppers but also their predators and when planthoppers re-emerged, they did so in even greater numbers. In response, the government banned some pesticides, eliminated subsidies for others and supported the roll-out of the Integrated Pest Management (IPM) programme to minimise pesticide use among rice farmers (Braun & Duveskog, 2008; Thorburn, 2014). Although the success of the IPM training is debated (Feder & Savastano, 2006; Thorburn, 2014), government support for the programme can be seen as a first large-scale attempt to establish more sustainable agricultural practices.

A prominent example of the negative environmental consequences resulting from measures undertaken to ensure food security is the ‘Mega Rice Project’. To make progress on rice self-sufficiency, the Suharto government ordered the conversion of one million hectares of peatland in Kalimantan into wet rice fields. Today, this project is largely regarded as an environmental disaster because it severely altered the hydrology of peatlands through canals and drainage which, in turn, made this area highly susceptible to fires and caused vast amounts of greenhouse gas emissions (Cattau et al., 2016; Goldstein, 2016).

The current agricultural system in Indonesia is associated with severe environmental challenges. The overuse of natural resources, the impairment of water and soil quality

and the degradation of the rich biodiversity all put pressure on the ecosystem. Intensive cultivation combined with high chemical fertiliser application has led to land degradation and a long-term decline in productive capacity. Excessive nitrogen fertiliser use is, for example, linked to reduced organic content in many rice fields and an increase in soil acidity (Nyi et al., 2017; Turmuktini, Simarmata, Joy, & Resmini, 2012). Substantial subsidies for fertiliser are believed to contribute to its inefficient use (Leimona et al., 2015; Osorio, Abriningrum, Armas, & Firdaus, 2011). These subsidies are partly driven by the goal of stimulating rice output and rice self-sufficiency. Yet, the effect of the subsidies seems limited as rice yields have stayed nearly constant in recent years despite substantial increases in fertiliser use (FAO, 2017).

Environmental problems also arise from Indonesia's high rate of deforestation. It threatens the country's biodiversity, reduces soil organic content and is part of the reason why Indonesia is one of the largest greenhouse gas emitters globally (Austin, Schwantes, Gu, & Kasibhatla, 2019). Most of its deforestation occurs in Sumatra and Kalimantan, driven by large plantations and logging companies as well as small-scale farmers (Cattau et al., 2016; Rudel, Defries, Asner, & Laurance, 2009). However, the relative share of deforestation caused by large-scale plantations has declined from around 50 percent in the early 2000s to around 25 percent in 2014-2016 (Austin et al., 2019). This development might in part be the impact of forest conservation policies that focused on large-scale plantations as well as the introduction of the Roundtable for Sustainable Palm Oil (RSPO) certification (Austin et al., 2019; Carlson et al., 2018). Next to logging, fire use is responsible for a substantial part of deforestation; reducing this is key to addressing Indonesia's emissions from the forest sector (Meehan, Tacconi, & Budiningsih, 2019). Despite several laws and regulations that ban it, the use of fire for land clearing remains high due its efficiency and cost-effectiveness compared to other practices (Medrilzam, Smith, Abdul, Herbohn, & Dargusch, 2017). Fire is also used to evade some of Indonesia's complicated policies regarding land and forest use. Studies suggest that the absence of land rights for local communities also contributes to deforestation and forest degradation (Jagger, Luckert, Duchelle, Lund, & Sunderlin, 2014; Watts et al., 2019).

Protecting Indonesia's forests is not only a step towards more environmentally sustainable agriculture but also affects the availability of critical eco-system services that play a role in production possibilities and human health. Yamamoto, Shigetomi, Ishimura, and Hattori (2019), for example, find that the loss of forest cover is negatively correlated with the agricultural productivity of non-estate crops, possibly due to its function as habitat for biological pest control. In addition to the severe negative public health effect from air pollution due to large-scale forest fires (Marlier et al., 2019), Garg (2019) finds that



primary forest loss in Indonesia is associated with an increased incidence of malaria in local populations.

The Indonesian government has recognised the need to make the agricultural system more sustainable. In 2011, the government released its first comprehensive plan to reduce emissions, the National Action Plan for Reducing Greenhouse Gas Emissions (RAN-GRK) (Meehan et al., 2019). However, Meehan et al. (2019), who evaluate the first phase from 2010-2014, conclude that there is little evidence that the RAN-GRK's actions were effective in reducing emissions. Indonesia's significance in terms of emissions from the forestry sector also made it a focus country for development activities within the United Nations Framework Convention on Climate Change (UNFCCC) programme for Reducing Emissions from Deforestation and Forest Degradation (REDD+).

In 2013, the government further released its first long-term agricultural development plan, the 'Grand Strategy of Agricultural Development 2013-2045' and declared the promotion of sustainable agroindustry to be its primary objective (FAO, 2017). In practice, the government has used a variety of policy instruments to reduce the impact of agriculture on the environment, including regulations and laws, economic incentives, mandatory sustainability standards for some products, information resources, and projects to promote agricultural systems such as organic farming (Anderson, Kusters, McCarthy, & Obidzinski, 2016; Glasbergen, 2018; Leimona et al., 2015).

The government has, for example, issued regulations and laws which ban the use of fire for land clearing as well as moratoria on new forest concessions for primary forests. However, enforcement of these bans has been challenging and the Indonesian government still struggles to reduce illegal land clearing and timber production (Leimona et al., 2015; Tacconi & Muttaqin, 2019). Since the early 2000s, the Indonesian government has also continuously promoted organic farming through programmes such as 'Go Organic 2010' and '1000 organic villages' (David & Ardiansyah, 2017). It has also started to increase its budget for organic fertiliser subsidies and, recently, the Minister for Agriculture recommended to reduce dependence on subsidised chemical fertilisers and increase the use of organic fertiliser during a programme for extension workers (Media Indonesia, 2020).

Yet, progress towards a more sustainable agricultural system is mixed and some policies and government activities appear at odds with each other. One example is the paradox between the commitment to make agriculture more sustainable and the ongoing substantial spending on chemical fertiliser subsidies. Studies have also highlighted the challenges that arise from the decentralised system and the lack of coordination as well as competing interests at different governmental levels. Anderson et al. (2016), for example, describe the contradiction between local plans to expand palm oil production to foster regional

development and provincial efforts for emission reduction in East Kalimantan.

Indonesia offers a particularly relevant setting to study how sustainable agricultural production can be enhanced. It is not only one of the most populous countries in the world with a large agricultural sector that provides income for millions, but also a global biodiversity hotspot with a large but declining share of land covered by tropical forest. As outlined, the current agricultural system has severe negative environmental impacts, locally and globally, and a transition towards a more environmentally sustainable system is needed. Furthermore, rapid urban growth and increases in per capita income have led to a growing number of ‘middle-income shoppers’ and potentially a growing local market for organic and sustainable products. Despite some contradictory policies and challenges in enforcing existing regulations, the Indonesian government shows commitment to addressing the negative impacts of agricultural production on the environment. This thesis aims to inform policies promoting this transition towards a more sustainable agricultural production system.

The results can potentially also inform policies in other parts of the world. The OECD-FAO Agricultural Outlook 2017-2026, for example, highlights the need to improve natural resource management and make agricultural production more sustainable as one of the key challenges for South East Asia in the coming years (OECD/FAO, 2017).

## 1.2 Literature Review

According to the FAO (2021), ‘to be sustainable, agriculture must meet the needs of present and future generations for its products and services, while ensuring profitability, environmental health and social and economic equity’. In practice, sustainable agriculture is commonly associated with a departure from input-intensive green revolution type technologies (D. R. Lee, 2005). Furthermore, sustainable agricultural practices are often characterised by a higher labour intensity, and benefits from their adoption, in particular for those focusing on soil rehabilitation, might require several years to materialise (Jayne, Snapp, Place, & Sitko, 2019; D. R. Lee, 2005). Practices that are commonly described as ‘sustainable’ include IPM, Integrated Soil Fertility Management (ISFM), Conservation Agriculture (CA) and organic farming (D. R. Lee, 2005). Yet, given the heterogeneity in contexts, what constitutes the most sustainable agricultural system varies (Kubitza, Krishna, Urban, Alamsyah, & Qaim, 2018; D. R. Lee, 2005; Mog, 2004).<sup>1</sup>

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<sup>1</sup>Consider the example of tropical forest protection. Reducing deforestation that occurs due to agricultural expansion is essential for the transition towards a sustainable agricultural system. A report by the FAO and UNEP (2020) estimates that between 2000 and 2010, 73 percent of deforestation resulted from agricultural expansion. Intensive farming which often provides lower levels of ecological functions but

In many cases, transitioning towards sustainable agricultural production requires farmers to change their practices. These changes can include the adoption of sustainable agricultural practices, water-saving, or the disadoption of excessive chemical input use or land burning. This links the question of how to promote sustainable agriculture to several strands of literature, including those on agricultural technology adoption and water and forest conservation.

The literature on agricultural technology adoption has identified information constraints, economic and credit constraints, risk, as well as behavioural factors such as procrastination as important barriers to adoption (for an overview see Bridle, Magruder, McIntosh, & Suri, 2020; Magruder, 2018). While a significant amount of research has focused on green revolution technologies, recent literature increasingly investigates the adoption of sustainable practices (e.g. Fisher, Holden, Thierfelder, & Katengeza, 2018; Hörner, Bouguen, Frölich, & Wollni, 2019; Maertens, Michelson, & Nourani, 2021; Wollni, Lee, & Thies, 2010).

Policymakers interested in making agricultural production more sustainable need to understand what enhances the uptake of sustainable practices and what is effective in reducing unsustainable practices. The following review discusses different instruments, broadly categorised into three types following the categorisation by Vedung (1998): legal and regulatory instruments, communicative and informational instruments and economic and market-based instruments. Rather than being exhaustive, it aims to provide a wider context for the papers contained in this thesis and highlight current research and debates.

### **1.2.1 Legal and Regulatory Instruments**

Policy makers can use legal and regulatory instruments to restrict or forbid agricultural practices. Regulatory interventions include the bans on fire use, logging, or pesticides as well as the introduction of protected areas and moratoria.

Land zoning divides land into zones with different rules and regulations and therefore allows to define protected areas or issue land use restrictions (Lambin et al., 2014). Meta-analyses show that, on average, protected areas tend to reduce deforestation and forest fires and protect biodiversity (Cazalis et al., 2020; Joppa & Pfaff, 2011). At the country level, Sims and Alix-Garcia (2017), for example, find that protected areas in Mexico were effective in reducing deforestation and achieved the protection of similar shares of land as simultaneously evaluated Payment for Ecosystem Services (PES) schemes.

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also demands less land, and ‘sustainable’ practices which provide higher levels of ecological functions but demand more land than present seemingly contradictory options for environmental conservation (Kubitza et al., 2018).

Evidence further suggests that, in practice, the combining of several policy instruments is common and often necessary to reach conservation goals (Agrawal, Hajjar, Liao, Rasmussen, & Watkins, 2018; Kubo, Wibawanto, & Rossanda, 2019). Kubo et al. (2019), for example, study the case of illegal logging in a national park in Kalimantan, Indonesia. The authors find that the regulatory approach in the form of capturing and punishing people decreased illegal logging in the short term but did not eradicate it. Instead, additional measures proved effective in supporting the regulatory approach, such as facilitation, visiting communities to explain the regulatory framework and financial support to start other businesses.

Citizens' attitudes towards sources of rules and regulation can also affect their response. In an experimental study on collective resource management in fishing villages in Sulawesi, Indonesia, Gallier, Langbein, and Vance (2018) compare responses to non-binding recommendations derived from three sources: from a democratic decision-making process, from group leaders and from external sources (e.g. an NGO). The authors find that only recommendations from external sources appear to strongly affect individual decision-making. However, this effect is concentrated in one research location. In the other two research locations, recommendations did not have a significant effect, irrespective of their source.

### **1.2.2 Communicative and Informational Instruments**

The FAO (2018) states that to 'build producers' knowledge and develop their capacities' is an activity central to transforming agriculture and achieving the SDGs. The importance of information and knowledge creation for agricultural technology adoption is also widely recognised in the academic literature (Foster & Rosenzweig, 1995; Jack, 2011; Magruder, 2018). D. R. Lee (2005) further argues that information and skill constraints are likely to be particularly relevant in the context of sustainable agricultural practices, as these are commonly very knowledge and skill-intensive.

The literature broadly differentiates between two types of information: (i) information about the profitability of a new technology (Besley & Case, 1994) and (ii) information about the optimal management of a new technology (Bandiera & Rasul, 2006; Foster & Rosenzweig, 1995). In the context of promoting sustainable agricultural technologies, we might also consider a third type of information, namely awareness of why current practices are unsustainable. Studying the adoption of soil conservation technologies in Tanzania and Thailand, Jones (2002), for example, finds that farmers' perception of soil degradation as a problem is essential for their intent to adopt remediating measures.

Agricultural extension programmes provided by governments or non-governmental organisations have long been the most frequently used tool to share knowledge and spread

new technologies, particularly in developing countries. Overall, experimental studies find a positive effect of information and skills training on the uptake of sustainable practices among smallholder farmers (e.g. Hörner et al., 2019; Kondylis, Mueller, & Zhu, 2017; Maertens et al., 2021). However, adoption estimates are often not generalisable across contexts, practices and modes of information and skill delivery. Maertens et al. (2021), for example, investigate the impact of farmer field days and demonstration plots on the adoption of ISFM practices among Malawian farmers. They find a positive effect for demonstration plots but not for the farmer field days. Interestingly, the authors also show that beliefs about the profitability of a technology, given farmer-specific constraints such as credit and labour, seem to influence farmers' knowledge scores for this technology after participating in extension activities.

Studies have also investigated whether information provision is effective in promoting the disadoption of excessive chemical input use. Reviewing interventions to reduce pesticide use among farmers in Europe, R. Lee, den Uyl, and Runhaar (2019) find that information-based instruments appeared most effective. In the context of Asia, evidence suggests that information provision reduced improper chemical fertiliser use in Bangladesh (Islam & Beg, 2020) and decreased chemical fertiliser use in China (Pan, Kong, Zhang, & Ying, 2017).

By whom and how information is delivered also matters. Krishnan and Patnam (2013) compare learning from neighbours and learning from extension workers and find that the initial impact of extension workers was high but wore off after some time, whereas the impact of learning from neighbours was more lasting. Evidence from studies which look at learning from contact farmers is mixed (Kondylis et al., 2017; Nakano, Tsusaka, Aida, & Pede, 2018). Findings by Shikuku, Pieters, Bulte, and Läderach (2019) from Uganda suggest that incentives for contact farmers can increase their efforts to diffuse climate-smart technologies; social recognition in the form of public valuation of their efforts increases their diffusion efforts, even more than the provision of financial incentives.

### **1.2.3 Economic and Market-Based Instruments**

Economic viability is essential for the adoption of sustainable agricultural practices (Glasbergen, 2018; Piñeiro et al., 2020). If externalities are positive but economic incentives are insufficient, this can lead to scenarios where sustainable agricultural practices are less widespread than is socially desirable (Shiferaw & Holden, 2000). This, in turn, provides a rationale for governments to pay farmers and communities for conservation, oftentimes implemented through PES schemes. Evidence from an RCT conducted in Uganda (Jayachandran et al., 2017) showed that a PES scheme was successful in reducing deforestation.

Studying farmers' motivation to join PES schemes for forest protection in Brazil, Zanella, Schleyer, and Speelman (2014) find that next to the information about the scheme, general environmental concern influences farmers' propensity to join such a scheme. This also links back to the argument in section 1.2.2 that information about why current practices are unsustainable matters in the context of sustainable agriculture.

While PES schemes, at least in theory, are based on conditionality, governments may also choose to provide farmers with unconditional conservation payments. Results from an RCT in Sierra Leone suggest that unconditional payments were not effective in reducing deforestation; instead, they even seem to have increased land clearing activities (Wilebore, Voors, Bulte, Coomes, & Kontoleon, 2019). The authors argue that a potential mechanism could have been the relaxation of economic constraints to hiring external labour for land clearing.

Market signals in the form of price premiums for sustainability certification can also create economic incentives. Certifications are generally based on the idea that consumers are willing to pay a price premium for certified products, based on their expectation that this price premium will ensure more environmentally friendly and socially responsible agricultural production (Agrawal et al., 2018; Glasbergen, 2018). Price premiums might be of particular relevance for technologies that are associated with lower output quantities or higher input costs due to increased labour requirements. Wollni et al. (2010), for example, find that organic market participation increased the number of soil conservation practices adopted by Honduran farmers. Ibnu et al. (2018) find that price premiums are the most important motivator for smallholders to participate in sustainable coffee certification schemes in Indonesia.

While Glasbergen (2018) questions the ability of international sustainability certifications to transform production systems, he highlights their role in creating awareness of sustainability aspects in agricultural production. This is reflected in efforts by developing country governments to create their own public sustainability standards. Despite being less stringent, Glasbergen (2018) argues that these could have a greater impact due to governments' legal enforcement power and the fact that these standards are often made mandatory. An example is the case of the Indonesian Sustainable Palm Oil standard. While less stringent than the RSPO standard, it is already mandatory for large-scale producers, and smallholders are required to comply by 2026.

## 1.3 Contribution

The literature review shows that there are a variety of instruments available to promote sustainable agriculture. Due to limits of generalisability, there is a need to study these instruments in a wider variety of contexts to assess whether they lead to similar results. Furthermore, some aspects such as the role of endorsement by non-traditional actors have received little attention so far. This thesis seeks to provide insights into the role of endorsement and information for sustainable agricultural production in Indonesia.

It comprises three self-contained papers which address the following questions: 1) Can faith-based endorsement by a religious institution encourage the disadoption of unsustainable practices? 2) Can hands-on training encourage the adoption of sustainable practices? 3) Is there local demand for certified organic food and can information increase the potential premium consumers are willing to pay?

The first paper explores the potential of religious endorsement for inducing pro-environmental behaviour and encouraging the disadoption of fire as an agricultural practice, thereby preventing forest fires. Forest fires are increasing in frequency and intensity in many tropical countries. This has detrimental effects on the environment and human welfare. Most of these fires are caused by human activities, such as land clearing, and there is a need to better understand how fires can be prevented. The paper analyses the impact of a fatwa (an Islamic religious ruling) on reducing fire incidence in Indonesia. The fatwa declares the burning of forests and land as forbidden and was issued by an important Indonesian Islamic organisation following the latest extreme fire season in 2015.

The paper shows empirically that fire incidence decreased in Muslim majority villages following the issuing of the fatwa. To analyse the impact of the fatwa, I employ a difference-in-difference approach with a matched sample and compare fire incidence in Muslim majority villages and non-Muslim majority villages before and after the fatwa was issued. I use an eight-year panel dataset that spans around 29,300 rural villages and combines village census data with remote sensing data on fires. For the post-fatwa period from August 2016 to December 2019, the average monthly effect amounts to around 2.2 prevented fire events per village. This is a considerable effect.

A major contribution of this paper is that it constitutes one of the first quantitative evaluations of the potential of faith-based support for environmental conservation. Despite a growing literature on conservation and numerous partnerships between faith-based organisations and conservation organisations, there is surprisingly little quantitative research on how effective the support of faith-based organisations is in changing environmentally-related behaviour. Findings from this paper imply that fire prevention efforts, and potentially other environmental conservation efforts, could benefit significantly from support

by religious institutions and stakeholders.

The second paper, co-authored with Michael Grimm, contributes to the literature on agricultural technology adoption and the literature on organic farming. While the first paper focuses on encouraging the disadoption of unsustainable practices, the second paper focuses on promoting the adoption of more sustainable practices. It investigates the role of information provision and training for the adoption of organic farming practices in Java, Indonesia. Previous studies highlighted information as an important driver of agricultural technology adoption. Yet, little is known about the effect of removing information constraints in the context of organic farming. Organic farming has many features that make it different from other technologies. It is often considered more labour intensive, the ultimate impact on productivity is uncertain and the short-term effects may be quite different from the long-term effects, as the regeneration of soils and consequent improvements in soil quality may take time. Furthermore, it is sometimes claimed that farmers do not need training as organic farming is the traditional way of farming.

In this paper, we conducted a randomised controlled trial (RCT) to identify the impact of three days of hands-on training in organic farming for smallholder farmers. The experiment was implemented in two regions in Java and encompassed 60 villages and 1,200 farmers. The training consisted largely of participatory practical sessions, for example on how to produce organic fertiliser, but also included some classroom sessions on organic principles.

We find that the training intervention increased the adoption of organic inputs and had a positive and statistically significant effect on farmers' knowledge and perceptions of organic farming one year after the training. Overall, our findings suggest that information constraints are a barrier to the adoption of organic farming, as information provision increased the use of organic farming practices. Endorsement may have also contributed to the impact of the training because the training may have influenced behaviour through an encouragement (or persuasion) effect. Endorsement of organic farming by an external trainer may have acted as a form of 'expert validation'. However, as expected, we cannot yet observe complete conversion to organic farming by farmers in the treatment group; rather it seems that a sizeable share of farmers in the treatment group has started to experiment with methods taught in the training while simultaneously continuing to use chemical inputs.

The third paper, co-authored with Michael Grimm and Franziska Steinhübel, shifts the focus from the supply side to the demand side. Sufficient local demand is an essential requirement for further adoption of organic farming by smallholders, who typically have limited access to export markets. The paper investigates whether local urban and



suburban consumers are willing to pay a price premium for organic food. The results suggest that there are opportunities to promote organic food locally and that consumers are willing to pay a premium for it. Like the second paper, the third paper explores the potential of information using a randomised information treatment. It analyses whether a low-cost information treatment can further increase the premium consumers are willing to pay. Previous literature suggests that environmental and health concerns motivate the purchase of organic food. However, our results provide no evidence that additional information on these food attributes significantly raises consumers' WTP.

We use an incentive-compatible auction based on the Becker-DeGroot-Marschak (BDM) approach to elicit consumers' WTP. Estimates suggest that consumers are willing to pay a price premium for organic rice; on average 20 percent more than what they paid for conventional rice outside of our experiment. We further find that higher income is correlated with a higher WTP. However, our results also indicate that raising consumers' WTP further is complex. Showing participants a video about the health or, alternatively, environmental benefits of organic food was not effective in further raising WTP. Exposure to the environmental benefits video was, however, effective in raising stated organic food consumption intentions. Until now only a few studies have explored local willingness to pay for organic products in low- and middle-income countries using a non-hypothetical experiment. So, this is one of the first studies to causally assess the effect of additional information (rather than pre-existing health or environmental concerns) on consumers' WTP for organic food. The results can be used as a basis for the design of alternative awareness measures to increase knowledge, interest and demand for organic food.

Together, the three papers in this thesis contribute to an understanding of possible pathways towards a more sustainable agricultural system in Indonesia, and potentially also in other regions of the world. The thesis shows that endorsement by institutions that influence norms and values in a society and hands-on practical training can contribute to the transition. Paper 1, in particular, makes the case to actively include a variety of actors in the efforts to promote sustainable agriculture. While information can play an important role, the thesis also shows that its effect is context-dependent and may not work in all forms. As paper 3 finds, low-cost information might not be sufficient to further increase the price premium consumers are willing to pay. Paper 3 does, however, also show the potential for farmers to obtain a price premium for organic food at local markets. Similar scenarios are likely in other emerging economies featuring a growing number of 'middle-income shoppers'.

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# 2 Can religion help to combat fire?

## Empirical evidence from Indonesia

*‘Effective partnerships between religious and conservation groups represent significant untapped potential which can directly support conservation outcomes.’ (Mcleod & Palmer, 2015)*

### 2.1 Introduction

Over the past few decades, forest fires have increased in both frequency and intensity (Jolly et al., 2015). These forest fires are primarily of anthropogenic origin, with land clearing fires used for agricultural purposes as one of the main contributors (Cammelli, Garrett, Barlow, & Parry, 2020; Cattau et al., 2016). In Indonesia, as in other tropical countries, changes in the climate and use of the land have increased the risk of land clearing fires burning out of control and causing large forest fires (Alisjahbana & Busch, 2017; Gaveau et al., 2014; Sloan, Locatelli, Wooster, & Gaveau, 2017). The detrimental effects of forest fires on the environment and human welfare have been well documented (Cammelli et al., 2020; He, Liu, & Zhou, 2020; Jayachandran, 2009; Kim, Manley, & Radoias, 2017; World Bank, 2016) and there is a growing body of research investigating the causes of these fires (e.g. Adrianto, Spracklen, Arnold, Sitanggang, & Syaufina, 2019; Cattau et al., 2016; Edwards, Naylor, Higgins, & Falcon, 2020; Sloan et al., 2017). Yet, despite the increasing prevalence of forest fires and the need to drastically reduce them, few rigorous evaluations have been devoted to investigating interventions that aim to reduce them.

This study aims to contribute to the understanding of fire prevention efforts by empirically evaluating the success of one particular intervention: the endorsement of fire prevention by a religious institution. Previous studies have argued that religion can help to communicate and legitimate conservation values, thereby shaping attitudes and conservation behaviour (Mcleod & Palmer, 2015; UNEP, 2016). In this study, I evaluate the impact of a fatwa, an Islamic religious ruling, on reducing fire incidence in Indonesia. Indonesia is a particularly interesting setting to study the potential of religious endorsement

for fire prevention as it is not only home to the world’s largest Muslim population but also one of the most fire-stricken regions in the world. The most recent extreme fire season, the el Niño year 2015, saw over 2.4 million hectares of land burned and is associated with more than half a million respiratory infections in Indonesia and Singapore (Alisjahbana & Busch, 2017; Koplitz et al., 2016; Sheldon & Sankaran, 2017). The following year, the Indonesian Council of Ulama (MUI), an influential Islamic clerical body, responded to a request from the Indonesian Ministry of Forestry to issue a fatwa on forest fires. This fatwa declares the burning of forest and agricultural land as haram and thus prohibited in Islam. I explore the potential impact of religious endorsement on environmental conservation by investigating whether this fatwa reduced the number of spatially observed fire events in Muslim majority villages in Indonesia.

While the majority of Indonesia’s population is Muslim, there is also a substantial non-Muslim minority which accounts for approximately 11 percent of the population. This study focuses on the two fire-prone islands Sumatra and Kalimantan. Importantly, both islands are characterised by some variation across villages regarding the main religion that most citizens adhere to. I exploit this geographical variation by differentiating between villages that report their main religion to be Islam and villages that report another religion as their main religion (mostly Christianity). The underlying assumption is that a fatwa issued by MUI has little effect on non-Muslim majority villages. Employing a difference-in-differences (DiD) design with a matched sample, I then investigate whether Muslim majority villages experienced a reduction in fires in the months following the issuing of the fatwa compared to their non-Muslim counterparts. I use an 8-year panel dataset spanning 29,300 rural villages and combine village census data with remote sensing data on fires. To this dataset, I further match remote sensing data on monthly rainfall, average monthly wind speed, yearly deforestation of intact and degraded primary forests, village area in proximity to palm oil plantations and village area covered by peatland. My empirical results show that the number of monthly fire events in Muslim majority villages decreased after the fatwa was issued. The average monthly effect equates to approximately 2.2 prevented fire events per village for the post-fatwa period (August 2016 to December 2019), this is a considerable effect. Results thus indicate that the fatwa was effective and supported forest fire prevention. However, regional poverty appears to weaken the impact of the fatwa. Robustness checks with two alternative treatment measures, the share of Mosques among a village’s religious buildings and the presence of non-formal Islamic schools, support the conclusion that the fatwa contributed to a reduction in fire incidence.

This study aims to make four contributions. First, to my knowledge, this is the first

study that rigorously evaluates the effect of a large-scale religious endorsement campaign on forest fire prevention. It also constitutes one of the first quantitative evaluations of the impact of religious endorsement in the context of environmental conservation more broadly. Partnerships between conservation organisations and religious bodies have increased over the past few decades. The Alliance of Religions and Conservations (ARC), for example, has implemented several projects, with organisations such as the World Wildlife Fund (WWF) and the World Bank. Additionally, in 2017, the United Nations Environment Programme launched its Faith for Earth programme. Case studies provide some evidence for the potential of these partnerships. For example, in Bali, Indonesia, local Hindu leaders supported a WWF-led campaign to stop the use of sea turtles in religious ceremonies (McLeod & Palmer, 2015) and in Tanzania, the WWF, ARC and Islamic Foundation for Ecology and Environmental Science collaborated to reduce the use of dynamite in fishing (Palmer & Finlay, 2004). McKay, Mangunjaya, Dinata, Harrop, and Khalid (2013) further find that water conservation-themed sermons increased the stated intention to act among Mosque attendees in Sumatra, Indonesia. Yet, despite a growing literature on conservation and numerous partnerships between faith-based and conservation organisations, there is little quantitative research investigating how effective the support of faith-based organisations is in changing environment-related behaviour.

Second, I contribute to the existing body of evidence on interventions that aim to reduce the use of fires for land-clearing and agricultural purposes. While there is a rapidly growing literature on interventions related to forest conservation (Jayachandran et al., 2017; Ngoma, Hailu, Kabwe, & Angelsen, 2020; Oliveira Fiorini, Mullally, Swisher, & Putz, 2020), empirical evaluations of interventions that specifically target fire prevention are more scarce. A notable exception is a recent study by Edwards, Falcon, et al. (2020) which evaluates the potential of collective payment for ecosystem services (PES) to reduce fire incidence in villages in Kalimantan, Indonesia. Despite a substantial payment accompanied by a comprehensive programme, the authors find no evidence for a significant reduction of fire frequency in response to the programme.<sup>1</sup>

Third, this study makes a methodological contribution by extensively assessing the robustness of results not only to different fire data sources but also to different fire event definitions. So far, only few economic studies using fire data account for the fact that several hotspots may belong to the same fire event. I compare various measurements of fire and other specifications using a specification curve analysis following Simonsohn, Simmons, and Nelson (2015, 2020).

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<sup>1</sup>In the context of individual incentive provision, He et al. (2020) find that a subsidy programme for straw recycling reduced straw fires in China and led to improved air quality and health benefits. However, their focus was not on the prevention of forest fires.

Fourth, existing studies have investigated the influence of Islam on Indonesian Muslims more generally (Bursztyn, Fiorin, Gottlieb, & Kanz, 2019; Pepinsky, Liddle, & Mujani, 2012), however, the extent to which their findings relate to MUI's influence is unclear. Non-quantitative studies highlight the potential of religious endorsement as moral support for government policies in Indonesia. The success of Indonesia's family planning programme, for example, is attributed partially to the changing attitudes of MUI and other Muslim organisations regarding birth control (Fraser, 2020; Menchik, 2014). Building on contributions by earlier studies regarding our understanding of MUI's role in Indonesia,<sup>2</sup> I aim to contribute to this literature by quantitatively assessing to what extent an MUI fatwa translates into everyday behavioural changes at the community level.

The remainder of this paper is structured as follows: Section 2.2 provides contextual information on fire and religion in Indonesia. Section 2.3 describes the data used. Section 2.4 explains the empirical approach and Section 2.5 reports the results. I provide a comprehensive set of robustness checks in Section 2.6. Section 2.7 discusses the results and Section 2.8 concludes.

## 2.2 Background: Forest Fires and Religion in Indonesia

### 2.2.1 Forest Fires

Forest fires are a recurrent phenomenon in Indonesia. Panel A of Figure 2.1 shows that fires in Sumatra and Kalimantan are concentrated during the dry season (August to October), although fires in Sumatra start a few weeks earlier than in Kalimantan.<sup>3</sup>

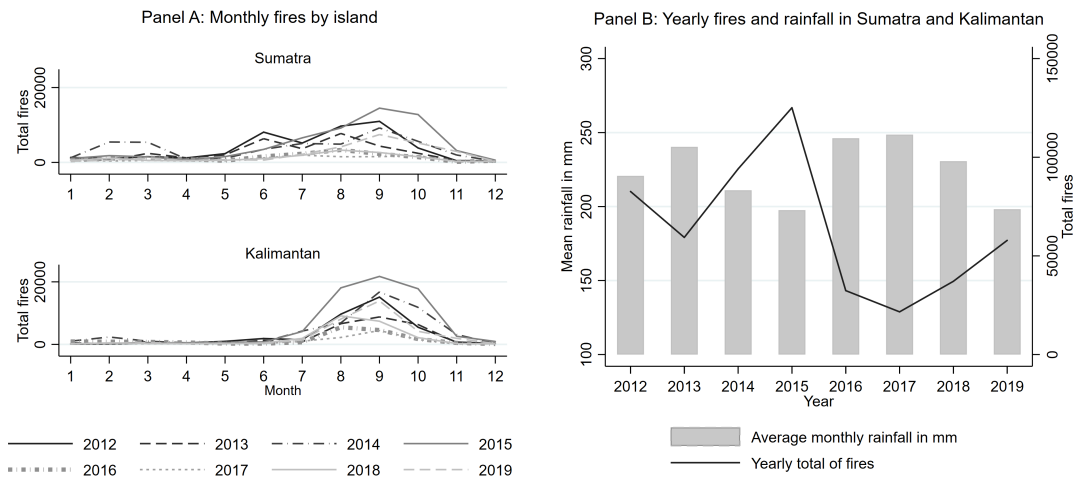
Fire seasons are particularly severe in el Niño years, i.e. years with higher than average temperatures and lower than average rainfall (Chen, Lin, Yu, & Lo, 2016; Shawki et al., 2017; Taufik et al., 2020). Panel B of Figure 2.1 depicts yearly fires and average rainfall for Sumatra and Kalimantan. Dry weather conditions amplify the frequency and duration of forest fires as fires spread more easily and are difficult to extinguish (Langner & Siegert, 2009). While large-scale forest fires were historically only associated with el Niño years, they are now also a common occurrence in non-el Niño years. This is largely attributed to climate change and to ongoing land-use changes, such as peatland drainage which is used to expand areas for farming (Gaveau et al., 2014; Sloan et al., 2017).

As in many parts of the tropics, most fires in Indonesia are anthropogenic, i.e. they are caused by human activities (Cattau et al., 2016; Santika et al., 2020). There is a long his-

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<sup>2</sup>See e.g. Menchik (2019), Mietzner and Muhtadi (2018) and Sirry (2013).

<sup>3</sup>The earlier start of the fire season in Sumatra is partially caused by a large section of the island being located north of the equator, where the dry season begins earlier (Shawki et al., 2017).



*Note:* Fire data is from the Viirs dataset. Fire detections were clustered into fire events using a 2Days x 2Pixels threshold (see Section 2.3). Rainfall measures the average monthly rainfall in mm in the respective year.

**Figure 2.1:** Fire patterns in Sumatra and Kalimantan

tory of land-clearing fires occurring in Indonesia and they are responsible for a large share of forest fire ignitions. As alternative methods are often costlier and more time-intensive, land clearing through fire remains a common practice (Adrianto et al., 2019; Medrilzam, Smith, Abdul, Herbohn, & Dargusch, 2017). While historically, they have mainly been used in swidden agriculture,<sup>4</sup> the large-scale use by various actors and the increasing use on peatland have exacerbated environmental consequences (Gaveau et al., 2017; Santika et al., 2020). Whether smallholder farmers or large companies are responsible for the largest share of fires remains a debated issue. Some studies find that most fires start inside or within close proximity of plantations, while others indicate that forest fires are closely associated with smallholder activities and local communities (Cattau et al., 2016; Gaveau et al., 2016; Santika et al., 2020; Sloan et al., 2017). Sloan et al. (2017), for example, find that proximity to palm oil plantations rather than land within plantations is associated with a higher frequency of fires. The authors suggest this is due to an increase in economic activity and a decrease in intact forests surrounding palm oil plantations. Examining the drivers of the 2015 fires at the village level, Edwards, Naylor, et al. (2020) find that proximity to forests, remoteness, customary land burning and poverty are all related to villages' fire propensity. Fire risk is also affected by regional governmental factors. After the creation of a new district, for example, fire incidence increases significantly in the newly created district (Edwards, Naylor, et al., 2020; MacDonald & Toth, 2019).

<sup>4</sup>Mertz et al. (2009) define swidden farming 'as land-use system that employs a natural or improved fallow phase, which is longer than the cultivation phase of annual crops, sufficiently long to be dominated by woody vegetation, and cleared by means of fire.'

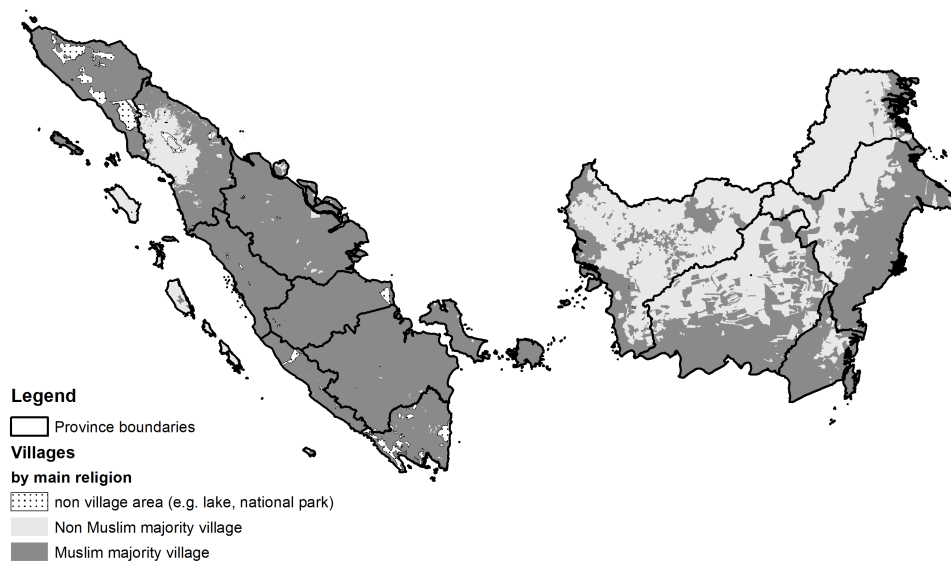
Human activities have also led to a significant increase in fire vulnerability in Sumatra and Kalimantan. Extensive logging and decades of draining peatland are two anthropogenic factors that indirectly cause forest fires (Alisjahbana & Busch, 2017). According to Nikonovas, Spessa, Doerr, Clay, and Mezbahuddin (2020), logging activities have a long-lasting effect on fire vulnerability as the originally fire-resilient primary forests become susceptible to fire when fragmented or deforested. Agricultural pressures have led to the clearing and drainage of peatlands, which has increased their susceptibility to fire (Sloan et al., 2017; van der Werf et al., 2008). As a consequence, fire on peatland has increased over the past few decades. These fires can continue to smoulder for days or weeks (Page et al., 2002; Santika et al., 2020). Peatlands have become a focus of fire prevention efforts because they contain large quantities of biomass and carbon, which is emitted when they are ignited (Cattau et al., 2016; Hooijer et al., 2010).

While Indonesia has implemented several measures over the past few decades and created a comprehensive regulatory framework to protect and restore forests, evidence suggests limited and mixed success (Alisjahbana & Busch, 2017; Tacconi, Rodrigues, & Maryudi, 2019; Uda, Schouten, & Hein, 2020). The Law on Forestry (No 4/2001), for example, prohibited all land and forest burning activities. However, other contradicting laws (including, for example, at the province level in Central Kalimantan) made exceptions for the use of controlled fires by smallholders. In response to the 2015 fires, President Jokowi issued a presidential decree (11/2015) which called upon regional governments to implement tougher fire prevention efforts. Yet, the reoccurring forest fires indicate that land and forest burning remain a common practice (Uda et al., 2020). Medrilzam et al. (2017) report that local actors are often critical of restrictions on land burning due to concerns for the livelihoods of smallholders. Indeed, Uda et al. (2020) find that burning remains a common practice despite its prohibition in Jambi and Central Kalimantan as it continues to be the fastest and cheapest method to clear land. Furthermore, deforestation and forest degradation through logging continue to occur at a large scale in forest types that are legally protected from land clearing (Hoare, 2015; Margono, Potapov, Turubanova, Stolle, & Hansen, 2014). In January 2016, President Jokowi issued a presidential decree establishing the Badan Restorasi Gambut (BRG), a peat restoration agency that works in several regions in Sumatra and Kalimantan. This is also part of Indonesia's commitment to the United Nations Framework Convention on Climate Change (UNFCCC) programme for Reducing Emissions from Deforestation and Forest Degradation (REDD+).



### 2.2.2 Religion: Fatwas and MUI

Islam is the prevailing religion in both Sumatra and Kalimantan. Figure 2.2 shows the spatial distribution of villages' main religion across both islands. In Kalimantan, Dayaks, who historically held animist beliefs but have largely converted to Christianity, tend to live in the forested interior of Kalimantan (Connolly, 2009). By contrast, Muslim Malays live largely in coastal areas. A different pattern emerges in Sumatra where Christians live mostly in central North Sumatra.



**Figure 2.2:** Spatial distribution of villages' main religion

Fatwas are commonly understood as Islamic religious rulings and are important elements of public debate in Indonesia (Menchik, 2019; Sirry, 2013). They are used to communicate Islamic rules and values to the general public (Menchik, 2019). Fatwa creation traditionally begins with a request for religious guidance. There are no restrictions on who can submit a request. Within Islamic organisations, a council of Ulamas (Muslim scholars) then discusses the request before potentially issuing a fatwa. The fatwa under evaluation in this study was issued by the Majelis Ulama Indonesia (MUI), which Lindsey (2012) describes as 'the most authoritative source of fatwa' in Indonesia.

MUI consists of Muslim scholars from various Indonesian Muslim organisations. However, it is not a representative umbrella organisation and other Islamic organisations continue to produce fatwas in parallel and even in competition (Lindsey, 2012). Founded in 1975 by President Suharto to control religious leaders, MUI has gained nominal autonomy from the state since Indonesia's democratisation and is increasingly shaping political and

public debate (Menchik, 2019). In contrast to other Muslim organisations, such as the world's largest Muslim organisations Nahdlatul Ulama (NU) and Muhammadiyah, which both have representatives within MUI, MUI itself has no membership network (Fraser, 2020). MUI fatwas are often issued to great media attention and, in recent years, MUI has increasingly employed mass mobilisation to assert its influence on policy makers (Lindsey, 2012; Menchik, 2019).

Fatwas themselves, including MUI fatwas, do not contain any sanctions. However, in some cases, MUI fatwas have influenced new laws and regulations (Hasyim, 2015; Menchik, 2019). The extent to which Indonesian Muslims consider fatwas as binding and as moral guiding principles seems to vary by topic and local leaders' and individuals' attitudes towards MUI and the particular fatwa (Menchik, 2019; Millie & Hindasah, 2015). An example of an MUI fatwa for which compliance is limited is the fatwa on smoking, which declares smoking in public as *haram*. Millie and Hindasah (2015) find that regional MUI branches do not always endeavour to disseminate fatwas from central MUI and sometimes even ignore them if they consider them not relevant to the local conditions (as was the case for the MUI fatwa on smoking).

MUI's active engagement with environmental topics preceded the fatwa on forest fires. In 2011, for example, MUI established the Institute for Environmental and Natural Resources (PLHSDA). In the same year, it also issued a fatwa on 'environmentally friendly mining' (Gade, 2015; Mangunjaya & Praharawati, 2019). In January 2016, the Ministry of Environment and Forestry made a request for religious guidance on the issue of forest and land burning. Following discussion within the Council of Ulama, a fatwa on this topic was officially released in July 2016 (Fatwa No 30/2016). The fatwa declares the burning of forests and land, which can cause damage, environmental pollution, personal loss, health problems and other adverse effects, as *haram*, i.e. forbidden according to Islamic beliefs. Furthermore, facilitating or deriving benefit from the burning of land and forest is also considered *haram* by the fatwa. It is important to note that this fatwa was issued in addition to existing laws and regulations which already restricted the use of fire.

In addition to MUI, various other actors have engaged in the dissemination of the fatwa, including government bodies at national and local levels and the newly established BRG (Mangunjaya & Praharawati, 2019). While there appears to be no official overview of dissemination activities, news articles report the distribution of thousands of posters, the publication of leaflets in public facilities such as mosques or village administration offices and training activities on the fatwa for local preachers.<sup>5</sup> However, Mangunjaya and

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<sup>5</sup><https://m.bidikonline.com/read-82343-2018-05-12-pemprov-riau-apresiasi-kerjasama-brg-bersama-mui.html>; <https://kalimantanpost.com/2020/07/bantu-cegah-karhutla-pt-bib-serahkan-fasilitas-sosialisasi/>; <https://www.jawapos.com/jpg-today/17/09/2019/lawan-karhutla-dishut-suntik-tanah>

Praharawati (2019) also state that the dissemination of the fatwa has been challenging and the ultimate level of individual and regional exposure to the fatwa remains unclear. Qualitative interviews conducted in Jambi (Sumatra) during an explorative study for this research further confirm the dissemination through various channels but also indicate heterogeneity in villagers' exposure to the fatwa. While some respondents heard about the fatwa in sermons, from social media or at village meetings, others were unaware of its existence. Respondents familiar with the fatwa had varying opinions regarding its effectiveness and whether it has the potential to affect citizens' attitudes towards land burning.<sup>6</sup>

## 2.3 Data

The panel dataset used in this study covers approximately 29,300 rural villages in the fire-prone islands Sumatra and Kalimantan. Village-level data comes from two rounds of the *Potensi Desa* (PODES), a village census conducted by the Indonesian Bureau of Statistics once every 3 to 4 years. To generate the panel dataset, I first created a boundary-consistent panel with the PODES 2014 and 2018 data. Overlaying these village boundaries on spatial datasets, I then merged the data with fire detections, population density, monthly rainfall, monthly average wind speed, peatland area, deforestation and palm oil concessions. This section describes each data source, outlines the data processing steps for the fire data and presents some summary statistics.

### 2.3.1 Socio-Economic Data: PODES, Population Density and Poverty

The PODES census covers all village-level administrative units in Indonesia and distinguishes between urban (*kelurahan*) and rural (*desa*) administrative units. For this study, I restrict the sample to rural villages as urban areas are rarely affected by agricultural land burning. Crucial to my analysis, the PODES census also provides information on the main religion practised in each village, as reported by the village head. Using this information, I distinguish between Muslim and non-Muslim majority villages. I use further information from the census on several other village characteristics, such as village

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[gambut-dan-sebarkan-fatwa-mui/](#) (accessed 6 February 2021).

<sup>6</sup>The interviews were conducted during the explorative study for this research project in February 2020 by two local enumerators. In total, 24 villagers from 12 villages were interviewed. One respondent described religion, for example, as an effective method to address land burning in a religious country like Indonesia, while another respondent reported that people do not care much about a fatwa on burning.

remoteness (distance to the nearest police station, material of the main street to the village), village development (main cooking fuel, electricity access) and whether agricultural burning is a common agricultural practice.

Given that the PODES data does not contain the villages' population size, I obtained 2014 population density data, i.e. people per square kilometre, at a resolution of 1 kilometre from the WorldPop data portal (Tatem, 2017). *Population* then measures the estimated village population in thousands and *Population density* measures people per square kilometre. I further use regional poverty estimates from the 2015 poverty and livelihood map by the SMERU Research Institute. The poverty headcount measures the share of citizens living below the national poverty line at the sub-district level.

Panel A of Table 2.1 presents descriptive statistics on socio-economic characteristics by main religion. Information from the PODES data comes from the 2014 census (the pre-fatwa baseline period). The data shows that Muslim and non-Muslim majority villages differ in several characteristics. Overall, non-Muslim majority villages are less populated, more remote (*Distance to police, Asphalt street*) and more likely to engage in customary agricultural land burning.

**Table 2.1:** Descriptive statistics by villages' main religion

	Muslim Majority village <i>Treated</i> <i>N = 23,997</i>		Non-Muslim Majority villages <i>Comparison</i> <i>N = 5,268</i>	
	mean	sd	mean	sd
<i>Panel A: Socioeconomic characteristics</i>				
Population (in thousands)	1.77	3.05	1.23	1.47
Population density (People per km2)	279.77	430.80	118.25	201.02
Poverty headcount as share	14.35	7.34	12.11	6.91
Agricultural burning is a customary practice (=1)	0.29		0.57	
Distance to the nearest police station (km)	8.34	11.38	16.93	21.46
Asphalt street to village (=1)	0.57	0.49	0.42	0.49
Share of HH with electricity	0.92	0.17	0.74	0.33
Wood is the main cooking fuel (=1)	0.38		0.66	
<i>Panel B: Fire characteristics</i>				
Mean monthly fire events 2002-2011	0.12	0.68	0.15	0.36
Any fire events 2002-2011 (=1)	0.49		0.56	
Mean monthly fire events pre-Fatwa	0.23	0.77	0.26	0.52
Mean monthly fire events post-Fatwa	0.10	0.33	0.19	0.39
Any fire event pre-Fatwa (=1)	0.53		0.67	
Any fire event post-Fatwa (=1)	0.43		0.58	
<i>Panel C: Environmental characteristics</i>				
Rainfall (mm/month)	216.32	34.33	259.95	41.58
Temperature (monthly mean)	26.33	2.73	25.19	2.26
Wind (seconds/metre)	1.77	0.63	1.61	0.47
Peatland share	0.05	0.19	0.02	0.11
Palm oil buffer share	0.21	0.33	0.14	0.28
Primary forest share 2012	0.09	0.21	0.27	0.34
Annual primary forest deforestation 2010-2019 (ha)	12.89	80.72	23.47	88.02

*Note:* Information on villages characteristics is from PODES is from the 2014 Census. *Agricultural burning is a customary practice, Asphalt street to village* and *Wood is the main cooking fuel* are binary variables.

### 2.3.2 Fire Data

I use two types of satellite-derived fire data, active fire data and burned area data. Active fires are determined through an elevated thermal radiance signal which identifies hotspots that are burning during satellite overpass and under relatively cloud-free conditions (Giglio, Schroeder, Hall, & Justice, 2018). I use active fire data from two sources, the Moderate Resolution Imaging Spectroradiometer (Modis) instruments (MCD14ML C7) and the Visible Infrared Imaging Radiometer Suite (Viirs) instruments (VNP14IMG). Both sources provide the location, time, date and confidence level of each detected hotspot. For data quality control, I drop hotspots classified as ‘low’ confidence (Giglio et al., 2018). The Modis data is available at a 1-kilometre resolution, i.e. each detected hotspot represents the centre of a 1x1 kilometre pixel which may contain several fires. The Modis instruments are on board NASA’s Aqua and Terra satellites which each overpass Indonesia twice a day. In total, there are four overpasses per day. Modis’ successor, the Viirs active fire data is available at an improved spatial resolution of 375-metre pixels but has a lower temporal resolution of two overpasses per day. For my main analysis, I use the Viirs data because of its improved spatial resolution and its ability to detect smaller fires (Vadrevu & Lasko, 2018). Modis active fire data is used as a robustness check.

Next to the active fire data, I use the Modis burned area product available at a 500-metre resolution as a robustness check (MCD64A1 C6). Burned area data is derived through a spectral reflectance-based change detection technique (Vadrevu & Lasko, 2018). It offers a robustness check to the active fire data as it is less time dependent; land-use changes persist over some time and can be detected at a later stage while active fire data can miss fires that burn for only a short period or fires covered by clouds at the time of satellite overpass. However, the burned area product is less well suited to detecting small fires as it requires a larger change in landscape (Zhang, Wooster, de Jong, & Xu, 2018).

In my main analysis, I focus on fire ignitions as an outcome rather than fire hotspots. While hotspots are of course closely related to fire ignitions, fire ignitions are the more relevant outcome of interest in the context of this study for two reasons. First, the focus on fire ignitions allows me to assign fires to the villages that were the ignition source. Consider, for example, a fire that ignites in one village but subsequently spreads to three other villages. If one measures fire frequency (i.e. hotspots), the village that is the ignition source and the three other villages will all be recorded as villages that experienced the fire. Conversely, by examining fire ignition, only the village that is the source of the fire would be associated with the fire event. Second, the extent of fire events, i.e. the number of hotspots or burned areas they comprise, is also influenced by aspects such as weather, soil conditions or local firefighting capacity. For example, if two villages report a fire

ignition on a given day and it rains the next day in one but not the other village, the first village will likely report fewer hotspots from the fire ignition. However, to evaluate the fatwa, both villages should be treated equally as citizens in both villages did not abstain from fire.

To group multiple hotspot detections into singular fire events and identify the ignition source, I first generated a spatial-temporal weights matrix using geospatial processing software. The spatial-temporal weights matrix generates a dyadic dataset on all relationships that fall within pre-specified time and distance windows (e.g. 2 days and 1 pixel). Based on the spatial-temporal weights matrix, fire hotspots were clustered into fire events (see Appendix A.1 for more details). For the burned area data, I employed the python package ‘firedpy’ to aggregate burned area pixels into distinct fire events.<sup>7</sup> For both data types, I then identified the earliest fire detection(s) within a fire event and, in line with Cattau et al. (2016), consider this to be the ignition of the fire event. This allowed me to trace the village where the ignition occurred.

Panel B of Table 2.1 provides descriptive statistics on fire ignition patterns by main religion. Fire events are based on Viirs hotspots which are clustered into fire events using a 2Days x 2Pixels time-space window. However, it should be noted that no one time-space window is optimal for all locations and fire events (Balch et al., 2020). Appendix A.2 provides a comparison of time-space windows and in Section 6 I address the robustness of the results to different time-space windows in greater detail. Large fire events can lead to tens or even hundreds of fire detections that belong to the same fire event; if they are all counted as individual events, the results could be distorted. Appendix A.2 shows that clustering reduces the number of observations with more than 10 fires per month and greatly reduces the number of observations with more than 100 fires per month. I further obtained data on historical fire prevalence to be included as one covariate in the matching process, which is described in Section 4. For historical fire prevalence in the pre-study period, I use Modis active fire data clusters by a 2Days x 1Pixel window as Viirs data is only available for the years since 2012. The pre-study period covers 10 years prior to the start of the study period in 2012.

During the pre-study period, more than half of the villages experienced no detected fire event, which illustrates that fire activity is locally concentrated. In the pre-fatwa period (January 2012 - July 2016), average monthly fire events were at 0.23 in Muslim majority villages and 0.26 in non-Muslim majority villages. This is much higher than in the post-fatwa period for both types of villages, but it is not surprising considering that

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<sup>7</sup>The open-source python command line interface is available at [www.github.com/earthlab/firedpy](http://www.github.com/earthlab/firedpy). The mechanism is described in Balch et al. (2020).

the pre-fatwa period included the extreme fire year of 2015.

### 2.3.3 Climate and Land Cover Data

*Rainfall* denotes the mean monthly rainfall in each village from satellite estimates. Rainfall data were sourced from the Tropical Rainfall Measuring Mission (TRMM), which is jointly operated by NASA and the Japan Aerospace Exploration Agency. I use the 3B43 monthly precipitation averages which are available at a 0.25-degree spatial resolution. *Wind speed* denotes average monthly wind speed. High wind speed can increase the spread of fires and make them difficult to extinguish. Surface level data on average monthly wind speed in metres per second were obtained from the National Oceanic Atmospheric Administration’s NCEP reanalysis products (Kalnay et al., 1996) at a spatial resolution of 0.5 degrees. *Peatland share* measures the share of village land covered by peatland. Data on peatland locations were obtained from the World Resource Institute’s Global Forest Watch database (Global Forest Watch, 2020). *Palm oil buffer share* captures the share of village land that lies within a 4-kilometre boundary area surrounding palm oil concession. As described in Section 2, previous studies report increased fire occurrences in proximity to palm oil concession. Data on palm oil areas based on Landsat data were sourced from Austin et al. (2017). *Primary forest share 2012* captures what portion of a village’s land was covered by primary forest at the beginning of the study period. Data on primary forests were obtained from Margono et al. (2014). As Indonesian forest regulations typically relate to primary forests and given the higher frequency of forest fires in primary forests (Nikonovas et al., 2020), I further estimated *Annual primary forest deforestation* at the village level. Following Santika et al. (2020), annual primary forest deforestation between 2010 and 2019 was estimated by overlaying spatial data of intact and degraded primary forests in Indonesia in 2010 provided by Margono et al. (2014) and the extent of annual forest loss provided by Hansen et al. (2013).<sup>8</sup>

### 2.3.4 BRG Programme

Data on the governmental programme for peatland restoration (BRG) were obtained from the programme’s website.<sup>9</sup> The initiative has established so-called ‘Peat Care Villages’, funded by the state, BRG partners and the private sector. These villages and information regarding the year in which activities began were matched to the panel dataset.

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<sup>8</sup>While the data is now available until 2019, the authors ask that their original paper is cited when the data is used.

<sup>9</sup><https://en.primis.brg.go.id/>

## 2.4 Empirical Strategy

### 2.4.1 Identification Strategy

This study analyses whether the MUI fatwa prompted a change in burning behaviours using a difference-in-differences (DiD) approach. Exploiting the variation in villages' main religions, I compare fire patterns between Muslim and non-Muslim majority villages before and after the issuing of the fatwa. My identification strategy relies on two critical assumptions. First, non-Muslim majority villages (the comparison group) are less affected by the fatwa. Although I cannot rule it out, it seems unlikely that individuals in non-Muslim majority villages would strongly respond to an MUI fatwa. Within Muslim majority villages, the effect of the fatwa on attitudes towards agricultural burning is expected to depend on the level of exposure to the fatwa, the individuals' relationship with religion, the subjective importance given to MUI and, potentially, the source which disseminates the fatwa (e.g. an influential local preacher). A change in attitudes at the community level could also create social pressure, making it less acceptable to engage in land burning. Whether a change in attitudes translates into a change in burning behaviours may further depend on other factors, such as economic pressures. As the fatwa appeals to moral values based on Islamic scriptures, it seems unlikely to have a strong effect on the attitudes and behaviours of non-Muslim Indonesians, especially considering the strained relationship between the Indonesian Christian minority and MUI.<sup>10</sup> Consequently, we may expect very little social pressure arising from the MUI fatwa in non-Muslim majority villages.

The second critical assumption for my DiD specification is that non-Muslim majority villages provide a valid comparison group and exhibit similar fire patterns in the pre-fatwa period. Hence, this common trend assumption imposes that, without the fatwa, Muslim and non-Muslim majority villages would have followed a common trend. Kahn-Lang and Lang (2020) further argue that next to common trends, DiD designs should also address differences in pre-treatment levels and whether this poses a risk to the identification. Panel A of Figure 2.3 visually examines this assumption and plots the pre- and post-fatwa averages for fire events in Muslim and non-Muslim majority villages. It shows that the two types of villages followed somewhat similar trends, with spikes in fire events occurring in the same months. However, levels are quite different. Furthermore, Table 2.1

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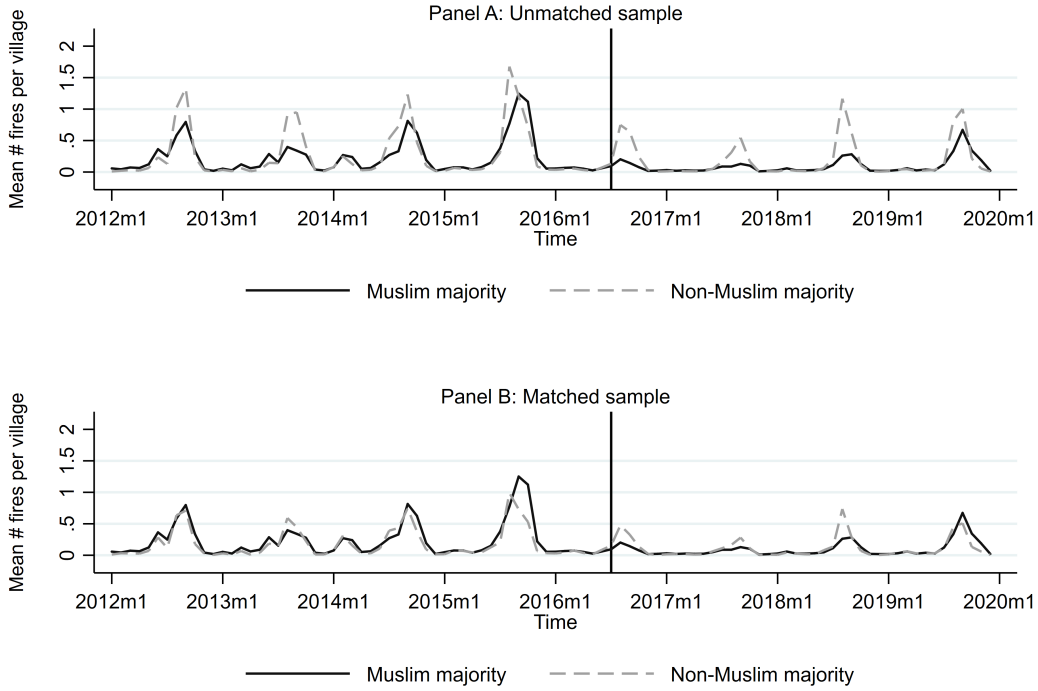
<sup>10</sup>Lindsey (2019) describes MUI as 'openly hostile to many religious, ethnic and social minorities' (p. 37). In 2005, for instance, MUI issued fatwas against religious plurality (Sirry, 2013). These fatwas have been used by radical Islamists to justify attacks on religious minorities, including Christians (Hefner, 2017). Furthermore, MUI is considered one of the key mobilisers in the protests against the Chinese-Indonesian Christian incumbent governor in Jakarta, 'Ahok', who was arrested for blasphemy following the protests (Mietzner & Muhtadi, 2018).



indicates that the two village types systematically differ in fire-related characteristics such as historical fire exposure, customary burning, peatland share, population density and remoteness. This may pose a problem to my identification if, for example, fire prevention efforts are concentrated in villages that have historically high levels of fire or high peatland shares.

To address this potential problem, I employ propensity score matching to generate a better comparison group of non-Muslim majority villages. The match was conditioned on covariates potentially related to the villages' fire propensity, namely population density, share of electricity, wood as main cooking fuel, poverty, distance to the next police station, material of the main road to the village, customary burning, and the share of village land covered by peat, primary forest and palm oil buffer zones. Furthermore, I include information on historical fire patterns in the 10 years prior to the study period (2002 - 2011). The choice of covariates relies largely on the existing literature on drivers of fire in Indonesia (e.g. Cattau et al., 2016; Edwards, Naylor, et al., 2020; Nikonovas et al., 2020; Santika et al., 2020; Sloan et al., 2017). The propensity scores thus reflect the differential propensity of villages to be a Muslim majority village based on these fire risk-related covariates. I then used nearest-neighbour matching with one neighbour and replacement to reweigh the non-Muslim majority villages and thereby create a more comparable control group. The distributions of the propensity scores in the Muslim and non-Muslim majority villages before and after matching are shown in Appendix A.3. Furthermore, Appendix A.4 reports the difference in mean values before and after matching for the variables the match was conditioned on. It further provides the standardised (percentage) bias (Rosenbaum & Rubin, 1985) to evaluate the matching performance. The reduction of mean standardised bias from 42 percent in the unmatched to 6 percent in the matched sample indicates a good matching outcome.

While the parallel trends assumption is not directly testable, Panel B of Figure 2.3 provides some evidence in support of this assumption in the matched sample, where pre-fatwa fire ignition trends and levels are closely aligned. The resulting panel of reasonably balanced villages allows for the identification of average responses and dynamics of the responses to the fatwa using the DiD and event study approaches. Nevertheless, some differences remain, such as differences in fire levels in the extreme fire year of 2015. To address this, I control for several time-varying factors that may influence fire patterns such as rainfall, primary forest deforestation rates and the interaction between peatland share and with rainfall.



Note: Fire data is from the Viirs dataset. Fire detections were clustered into fire events using a 2Day x 2Pixels threshold (see Section 2.3).

Figure 2.3: Fire trends before and after matching

## 2.4.2 Econometric Specification

First, I study the average monthly response to the fatwa using the following specification:

$$y_{vpm_y} = \beta_1(treat_v * post_{my}) + \delta_{my} + \gamma_v + P_{pym} + P_{pm} + B_{vpy} + X_{vpm_y} + \epsilon_{vpm_y} \quad (2.1)$$

The dependent variable  $y_{vpm_y}$  is the number of fire ignitions in village  $v$  in province  $p$  in month  $m$  and year  $y$ . The variables  $treat_v$  and  $post_{my}$  are binary indicators which take the value 1 for all villages where the main religion is Islam and all months after July 2016,<sup>11</sup> respectively.  $\beta_1$  then captures the average monthly post-fatwa reduction of fire ignitions in Muslim majority villages (compared to the benchmark period January 2012 to July 2016), relative to the post-fatwa change in fire ignitions for the matched comparison group.  $\delta_{my}$  is a vector of month-by-year fixed effects to control for factors affecting all villages. The panel data dimension further allows controlling for time-invariant village

<sup>11</sup>Theoretically, the fatwa could already have impacted fire behaviour before it was issued, during the months it was discussed. To my knowledge, there is no reliable documentation on this. Yet, if this was the case, it would likely reduce the magnitude of the estimated coefficient.

fixed effect,  $\gamma_v$ , including long-term climatic and environmental conditions as well as cultural and historical aspects. Province time trends,  $P_{pyt}$ , account for province-specific linear time trends in fire patterns while province-month fixed effects,  $P_{pm}$ , account for the regional differences in seasonal fire activity, for example, the fire season beginning earlier in some regions than in others.  $B_{vpy}$  is a binary indicator which takes a value of 1 if village  $v$  was part of the BRG programme in year  $y$ . In addition,  $X_{vpy}$  is the time-variant control vector covering whether monthly rainfall was above 200 mm, whether average rainfall in the preceding 3 months was above 200 mm, monthly average wind speed, the interaction between rainfall indicators and villages' peatland share and the interaction between  $post_{my}$  and distance to the nearest police station. Sloan et al. (2017) find that the effect of rainfall on fire risk is non-linear. The authors identified 200 mm per month as a critical threshold. The peatland interactions account for the possibility that rainfall has a differential effect on peatland fire propensity, while the distance to police interaction accounts for changes related to remoteness that occurred at the same time as the fatwa. This relates, for example, to a potential increase in law enforcement efforts due to the presidential decree (11/2015). If villages are located far from a police station, it may be more difficult to enforce restrictions on fire use. Finally,  $\epsilon_{vpy}$  is the idiosyncratic standard error adjusted for heteroscedasticity and clustered at the village level to allow for serial correlations within each village.

Second, I employ an event study approach to study the dynamics of fire prevention responses with the following distributed lag model:

$$y_{vpy} = \sum_{m=-54}^{41} \beta_t(\text{treat}_v * \text{post}_{my}) + \delta_{my} + \gamma_v + P_{pyt} + P_{pm} + B_{vpy} + X_{vpy} + \epsilon_{vpy} \quad (2.2)$$

Coefficients  $\beta_1 \dots \beta_{41}$  measure the additional marginal response 1 to 45 months after the fatwa was issued. Similarly, coefficients  $\beta_{-54} \dots \beta_{-1}$  capture the trend differences in fire ignitions between the treatment group and the comparison group in each of the pre-fatwa months. It may, for instance, be the case that it took some time until the fatwa was disseminated which, in turn, could have caused a delay in its impact. Yet, it could be that the fatwa only had a short-term impact on fire patterns. The event study approach allows investigating this further. Equations 2.1 and 2.2 are estimated using a linear fixed-effects model.

## 2.5 Results

### 2.5.1 Effect of the Fatwa on Monthly Fire Ignition

I begin by estimating the average response to the fatwa in terms of monthly fire ignitions at the village level. Table 2.2 reports the results of the DiD model (see Eq. 2.1) applied to the matched monthly panel data. If the fatwa was successful in affecting people's fire-related behaviours towards a lower fire usage, we would expect the interaction term *Fatwa*  $\times$  *Muslim majority village* to be negative. As the first row of Table 2.2 shows, the interaction term is indeed negative and statistically significant at the 1 percent level in all specifications. Column (1) shows the estimation results on the simple baseline model considering only the effect of the fatwa on Muslim majority villages, monthly rainfall and rainfall in the three preceding months. The results remain robust to adding province time trends and province by month fixed effects (see Column (2)) and further control variables (see Column (3)). The negative coefficient on the effect of the fatwa decreases only slightly in absolute terms and remains statistically significant at the 1 percent level.

The coefficient of interest in Column (3) suggests that the fatwa reduced the number of monthly fire ignitions by 0.053 events. Considering that the average number of fire events in the matched group of non-Muslim majority villages was 0.1 in the post fatwa period, this effect is considerable. Multiplying the average monthly effect with the 41 post-fatwa months yields approximately 2.2, i.e. a total reduction of 2.2 fire ignitions in Muslim majority villages for the post-fatwa period (August 2016 to December 2019).

The directions of the other coefficients are also largely in line with expectations. The negative correlation with rainfall can be explained by a reduction of flammability under high precipitation conditions and a higher probability that smaller fires extinguish before the next satellite overpass. Similarly, the positive correlation between wind speed with the number of observed fire events can be explained by an increase in fire spread and the difficulty in extinguishing fires created by high wind speeds. The negative and statistically significant coefficient for the BRG variable suggests that fire ignitions decreased in villages with programme activities. In contrast to previous studies (e.g. Nikonovas et al., 2020), Columns (2) and (3) provide no evidence for a strong correlation between the number of observed fire events and past primary forest deforestation. However, it should be noted that the model only accounts for deforestation in the previous year as the temporal sequence of fire ignition and deforestation in the same year cannot be determined with the yearly deforestation data.

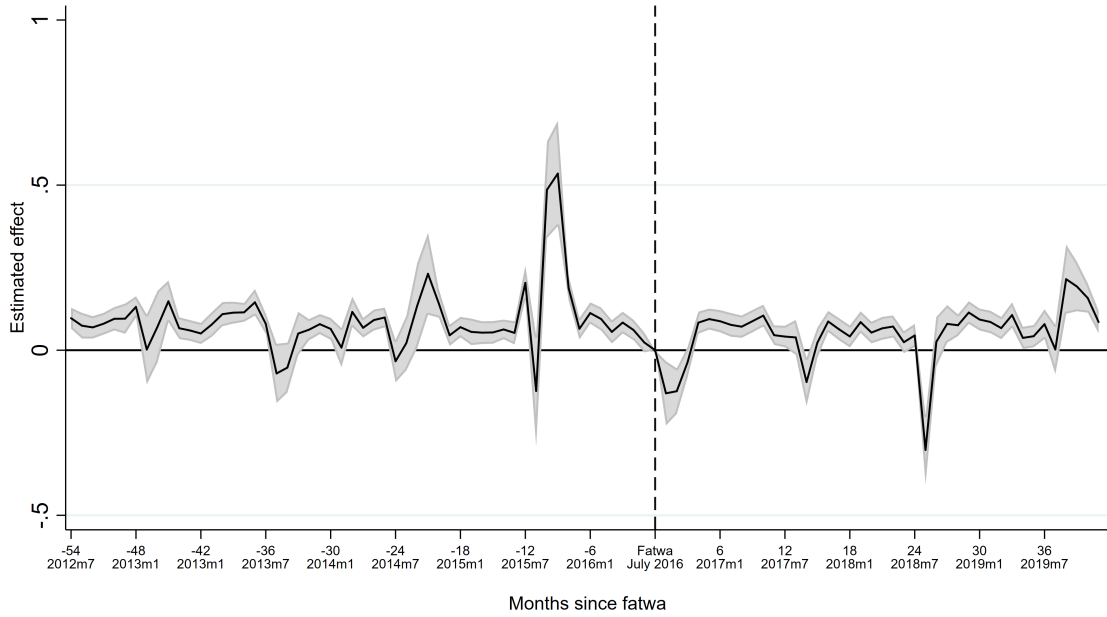
**Table 2.2:** Impact of the fatwa on monthly fire ignitions

	Monthly fire ignitions		
	(1)	(2)	(3)
Fatwa × Muslim majority	-0.060*** (0.000)	-0.060*** (0.000)	-0.053*** (0.000)
Rainfall (+200 mm)	-0.225*** (0.000)	-0.091*** (0.000)	-0.050*** (0.000)
Rainfall 3-month lag (+200 mm)	-0.009 (0.276)	-0.023*** (0.000)	0.010 (0.159)
Wind	0.128*** (0.000)	0.078*** (0.000)	0.078*** (0.000)
Fatwa × Distance to police			-0.005*** (0.000)
BRG			-0.395*** (0.001)
Primary forest deforestation lag (1 year)			0.000 (0.824)
Peat × Rainfall (+200 mm)			-0.545*** (0.000)
Peat × Rainfall 3-month lag (+200 mm)			-0.711*** (0.000)
Mean monthly fire ignitions in the post fatwa period in the matched comparison group: 0.10			
Village fixed effects	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes
Province-time trend	No	Yes	Yes
Province-month fixed effects	No	Yes	Yes
Observations	2,651,712	2,651,712	2,651,712
Number of villages	27,622	27,622	27,622
R-squared	0.037	0.101	0.105

*Note:* Fire ignitions are derived from the Viirs active fire data with a 2Days x 2Pixels time-space window. The matching method used is nearest neighbour (1:1 with replacement). Robust p-values in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## 2.5.2 Event Study Approach

Using July 2016, i.e. the month the fatwa was issued, as the reference month, I compare the changes in the number of fire ignitions between Muslim and non-Muslim majority villages relative to July 2016. Figure 2.4 displays the estimated coefficients on the Muslim majority interaction for each month. In the pre-fatwa period, these estimated coefficients vary considerably and are mostly positive or not statistically significant. Following the issuing of the fatwa, there remains variation but estimated coefficients are much smaller and become negative and statistically significant for the months 1, 2, 13 and 25 after the fatwa was issued, i.e. September and August 2016, August 2017 and August 2018. By 2019, however, the estimated coefficients increase again. Overall, the observed pattern provides no evidence that the effect of the fatwa was restricted to the months immediately following its issuing. Unfortunately, there are no records on when dissemination efforts for the fatwa peaked. However, records show that they were still ongoing in 2018.



*Note:* The figure provides a graphic analysis of the effect of the fatwa on monthly fire ignitions at the village level. The figure plots the estimates  $\beta_t$  from Equation 2.2.

**Figure 2.4:** Event study of fatwa impact on fire ignition

### 2.5.3 Heterogeneity

The results shown in Table 2.2 indicate that, on average, the fatwa reduced fire ignitions in Muslim majority villages. However, this effect likely masks considerable heterogeneity in villages’ responses to the fatwa. One question for interrogation includes whether this effect is stronger when citizens are more religious or weaker when citizens face higher economic pressures.

Measuring the influence of religion and, in particular, the influence of MUI in the respective villages is challenging. The number of mosques in a village can serve as a potential proxy for the influence of Islamic leaders. A high density of mosques may reflect higher local demand for religious services and could also indicate that the village population is more frequently exposed to religious teaching, including the spreading of information concerning issued fatwas. Column (1) of Table 2.3 reports estimates regarding whether the effect of the fatwa differed depending on the number of mosques per village. Considering the heterogeneity in village size, population density and remoteness, it is misleading to simply examine the number of mosques per village. Villages with more citizens are likely to have more mosques. Similarly, if the population is very dispersed across the village area, i.e. population density is low, more mosques may be built to allow citizens easy access to a mosque for daily prayers. The regression provided in Column

(1) therefore controls for these factors (by including an interaction term with *Fatwa* and a triple interaction term with *Fatwa*  $\times$  *Muslim majority village* for each factor). The coefficient *Fatwa*  $\times$  *Muslim majority village*  $\times$  *Mosques* measures whether the effect of the fatwa differed depending on the number of mosques per village, holding village population size, population density and distance to the nearest police station constant. The estimated coefficient is not statistically significant, indicating that the magnitude of the fatwa’s effect does not depend on the number of mosques per village.

Several factors may explain this. First, it could be that the number of mosques per village is not a good proxy for religiosity. Unfortunately, the village census data provides no insight into individual piety. Second, the impact of the fatwa may be more dependent on the local influence of MUI than on religiosity or exposure to formal religious teaching in mosques. Third, the fatwa may have been disseminated primarily through other channels besides sermons and other mosque-related activities. Fourth, factors such as villagers’ pre-existing awareness of the negative externalities of land burning and the attitude of the local imams and influential stakeholders towards MUI and the issue of land burning and environmental protection may be relevant for the effect of the fatwa.

To explore the dependence of the fatwa concerning economic pressures, I consider the effect of the fatwa given different levels of regional poverty. The second column of 2.3 provides evidence that higher regional poverty weakens the effect of the fatwa. To isolate the effect of poverty, I again include controls for population size, population density and distance to the nearest police station. It should be noted that this may partially absorb the poverty effect. The coefficient for the triple interaction term *Fatwa*  $\times$  *Muslim majority village*  $\times$  *Poverty* in Column (2) is statistically significant and the magnitude of the estimate suggests that an increase in the share of people below the poverty line by 1 percentage point, lowers the magnitude of the fatwa effect by around 0.004. To put this into perspective, one may examine the example of two villages, one located in a sub-district with a 10 percent poverty headcount rate and the other located in a sub-district with a 15 percent poverty headcount rate. The expected effect of the fatwa would then be lower by 0.02 in absolute terms in the latter sub-district. This finding is in line with the hypothesis that poverty reduces people’s ability to abstain from land burning in a context where alternative land clearing methods remain more expensive.

Next to poverty, economic incentives may create economic pressure and influence the fatwa’s impact. The increase in economic activity in the surrounding of palm oil plantations, for example, was identified as one driver of fire incidence (Sloan et al., 2017). In these areas, high economic incentives from land clearing may reduce citizens’ willingness to change land burning behaviours in response to the fatwa. To test this, I overlay the

fire data with the data on 2015 palm oil plantations and distinguish whether the fires occurred within a 4-kilometre radius of a palm oil plantation. I then use monthly village fires which occurred in palm oil plantations’ surroundings as an outcome variable. Column (3) in Table 2.3 shows the results. The estimated coefficient for *Fatwa × Muslim majority village* is negative and statistically significant, indicating that the fatwa was also effective in reducing the number of fire ignitions occurring in the surrounding of palm oil plantations.

**Table 2.3:** Heterogeneity in the impact of the fatwa on monthly fire ignitions

	Monthly fire ignitions (all)		Monthly fire ignitions (palm oil surroundings)
	(1)	(2)	(3)
Fatwa × Muslim majority	-0.050*** (0.007)	-0.081** (0.029)	-0.021*** (0.000)
Fatwa × Muslim majority × Mosques	0.009 (0.105)		
Fatwa × Mosques	-0.002 (0.745)		
Fatwa × Muslim majority × Poverty		0.004*** (0.001)	
Fatwa × Poverty		0.004*** (0.000)	
Mean monthly fire ignitions in the post fatwa period in the matched comparison group: 0.10			
Mean monthly fire ignitions in the post fatwa period in palm oil plantations’ surroundings : 0.04			
Village fixed effects	Yes	Yes	Yes
Year-month fixed effects	Yes	Yes	Yes
Province-time trend	Yes	Yes	Yes
Province-month fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	2,651,712	2,651,712	2,651,712
Number of villages	27,622	27,622	27,622
R-squared	0.110	0.109	0.068

*Note:* Controls include the share of months with rainfall below 200mm, average monthly wind speed, BRG dummy, Fatwa × Police, Peatland share × share of months with rainfall below 200mm. Fire ignitions are derived from the Viirs active fire data with a 2Days × 2Pixels time-space window. For Columns (1) & (2), controls further include interactions with Fatwa and triple interactions with Fatwa × Muslim majority for the factors Population, Population density and Distance to police. In Column (3), the outcome refers only to fires that occurred in palm oil buffer zones. The matching method used is nearest neighbour (1:1 with replacement). Robust p-values in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## 2.6 Robustness Checks

### 2.6.1 Alternative Outcome: Agricultural Burning

As an alternative outcome variable, i.e. one that should also be affected by the fatwa, I use the village heads’ reports on customary agricultural burning in their village. I have two observations; one from the PODES 2014, which falls into the pre-fatwa period, and one from the PODES 2018, which falls into the post-fatwa period. The results in Table



2.4 Column (1) indicate that the fatwa reduced the probability of village heads reporting agricultural burning as a customary practice by 13.4 percentage points in Muslim majority villages. The results remain robust to the addition of control variables in Column (2). The coefficient is negative and statistically significant at the 1 percent level in both, Columns (1) and (2). To compare the results, Columns (3) and (4) provide estimates with averaged monthly fire events as an outcome, i.e. a panel length of only two time periods with one pre-fatwa and one post-fatwa observation. The results for the alternative outcome ‘reported customary agricultural burning’ support the main results. However, I cannot rule out that answers by village heads in Muslim majority villages may have suffered from social desirability bias in 2018.

**Table 2.4:** Impact of the fatwa on agricultural burning

	Agricultural burning		Monthly fire ignitions	
	(1)	(2)	(3)	(4)
Fatwa × Muslim majority	-0.134*** (0.000)	-0.128*** (0.000)	-0.060*** (0.001)	-0.034*** (0.001)
Village fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	No	Yes	No
Province-time fixed effects	No	Yes	No	Yes
Controls	No	Yes	No	Yes
Observations	55,244	55,244	55,244	55,244
Number of villages	27,622	27,622	27,622	27,622
R-squared	0.037	0.064	0.055	0.187

*Note:* Controls include the share of months with rainfall below 200mm, mean monthly temperature, Wind, BRG dummy, Fatwa × Police, Peatland share × share of months with rainfall below 200mm. The matching method used is nearest neighbour (1:1 with replacement). Robust p-values in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## 2.6.2 Alternative Treatment: Share of Mosques and Non-Formal Islamic Schools

To explore to what extent the results depend on the definition of the treatment variable, I consider two alternatives: (i) the share of Mosques among all religious buildings within a village and (ii) the presence of a non-formal Islamic school. The voting share for Islamic parties during regional elections was also considered but not deemed suitable to measure religiosity or MUI influence as nationalist parties also run on religious platforms in Indonesia.<sup>12</sup>

<sup>12</sup>According to Pepinsky (2020), in Indonesia ‘voting for an Islamic party is not always a vote for Islam, and voting for a non-Islamic party sometimes is.’ The Indonesian nationalist party Golkar, for example, is particularly popular among religious Muslims outside of Java because it frequently puts Islamic regulations into practice (Buehler, 2013).

Ideally, I would have data on the exact share of Muslims within a village. Unfortunately, the PODES census only provides information on the main religion. It does, however, provide information on the number of different types of religious buildings and I use this information to create a proxy for faith composition. I create the categorical variable *share of Mosques* denoting whether the fraction of Mosques among all religious buildings is less than 10, 10 - 30, 30 - 50, 50 - 70, 70 - 90 or more than 90 percent. To account for the heterogeneity in pre-fatwa trends across groups, I restrict the sample to villages with an average of at least 2 yearly fires during the pre-study period (2002 - 2011) and include interactions between  $post_{my}$  and the variables included in the propensity score matching to control for remaining differences (see Appendix A.5 for a more detailed discussion).

The second alternative treatment measure, *non-formal Islamic education*, is a binary variable indicating whether there is a Madrasah Diniyah (school offering afternoon Islamic classes) or a Pesantren (Islamic boarding schools) in the village. The presence of non-formal Islamic education may indicate a higher exposure to religious leaders and content. However, two important aspects should be noted. First, this measure does not account for whether a village has an Islamic school that is part of the formal education system. In terms of formal education, the PODES data only distinguish between private and public schools, yet both types encompass religious and non-religious schools. Second, it is uncertain whether the presence of a non-formal school reflects a higher MUI influence as MUI itself plays no major role in the Indonesian education system. Similar to the approach described for the main treatment variable, I employ propensity score matching to address heterogeneity in pre-fire trends and create a better comparison group (see Appendix A.6 for more details).

Table 2.5 reports the results for the alternative treatment measures. The results show that villages with a higher Mosque share (Column (1)) and villages with at least one non-formal Islamic school (Column (2)) experienced relative fewer fires in the months following the fatwa. This adds further confidence to the robustness of the main findings.

### 2.6.3 Placebo Outcome

A key concern when evaluating treatment effects using DiD is whether the treatment could be correlated with unobserved variables which affect the outcome. Following the extreme fire season in 2015 and the accompanying deforestation, Indonesia experienced not only political pressure from neighbouring countries affected by the haze and other international stakeholders but also committed to the Paris Climate Agreement and to further actions in the context of REDD+. We may thus be concerned that the reductions in fires were caused by unobserved factors and remaining imbalances that drive, for example, a differential

**Table 2.5:** Alternative treatment measures

	Monthly fire ignitions in villages with average yearly historical fires >2	Monthly fire ignitions in matched sample
	(1)	(2)
Reference category: Mosque share <10%		
Fatwa × Mosque share 10% - 30%	0.023 (0.568)	
Fatwa × Mosque share 30% - 50%	-0.085** (0.023)	
Fatwa × Mosque share 50% - 70%	-0.289*** (0.000)	
Fatwa × Mosque share 70% - 90%	-0.296*** (0.000)	
Fatwa × Mosque share >90%	-0.379*** (0.000)	
Fatwa × non-formal Islamic school		-0.022** (0.015)
Village fixed effects	Yes	Yes
Year-month fixed effects	Yes	Yes
Province-time trend	Yes	Yes
Province-month fixed effects	Yes	Yes
Controls	Yes	Yes
Fatwa interactions	Yes	No
Observations	419,328	2,678,688
Number of villages	4,368	27,903
R-squared	0.210	0.123

*Note:* Fire ignitions are derived from the Viirs active fire data with a 2Days x 2Pixels time-space window. For Column (2), the matching method used is nearest neighbour (1:1 with replacement). Robust p-values in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

impact of law-enforcement in Muslim and non-Muslim majority villages. To address this concern, I implement a placebo test with yearly deforestation of primary forest at the village level as a placebo outcome. To isolate the effect of deforestation through logging, I control for observed fire hotspots. Primary forest deforestation through logging provides a useful placebo outcome as it is affected by many of the same mechanisms as deforestation through fires. This includes regulations that prohibit both activities as well as potentially changing perceptions of forest conservation at local and regional levels.

Table 2.6 shows the results of the placebo test. I differentiate between all primary forests (intact and degraded) and intact primary forests as conservation efforts and law enforcement could be more stringent for the latter. I expect that the coefficient for the treatment effect would also be statistically significant and negative for the placebo outcomes if the treatment effect reflects stricter law enforcement or higher conservation efforts rather than the fatwa itself. However, the interaction term *Fatwa × Muslim majority* is not statistically significant in Columns (1) and (2). The absence of significant effects of the treatment on the placebo outcomes provides further evidence supporting the validity of the main finding that the fatwa was successful in reducing fire ignitions.

**Table 2.6:** Impact of the fatwa on placebo outcome

	Primary forest deforestation	Intact primary forest deforestation	Monthly fire ignitions
	(1)	(2)	(3)
Fatwa $\times$ Muslim majority	2.064 (0.366)	-0.001 (0.990)	-0.044*** (0.001)
Village fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Province-time trend	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Fire hotspots	Yes	Yes	No
Observations	220,976	220,976	220,976
Number of Villages	27,622	27,622	27,622
R-squared	0.021	0.003	0.067

*Note:* The dependent variables 'Primary forest deforestation' and 'Intact primary forest deforestation' measure the yearly, village level deforestation of the respective forest type in ha. The Hotspots are derived from the Viirs data. Controls include the share of months with rainfall below 200mm, mean monthly temperature, mean monthly wind speed, BRG year dummy, Fatwa  $\times$  Police, Peatland share  $\times$  share of months with rainfall below 200mm. For Column (3) controls also include lagged primary forest deforestation. The matching method used is nearest neighbour (1:1 with replacement). Robust p-values in parentheses, \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

### 2.6.4 Specification Curve Analysis

Next, I employ a specification curve analysis to investigate the sensitivity of the estimated treatment effect to different specification choices. The specification curve analysis was introduced by Simonsohn et al. (2015, 2020) as a tool for research transparency. By visualising how different specification choices may have affected the results, it allows for an examination of the findings' dependence on my specification decisions leading to the results in Table 2.2. For this purpose, I consider four dimensions along which specification decisions can differ: outcome definition, panel length, choice of matching method and choice of covariates. The specification possibilities for each dimension and their possible combinations yield a total of 2,082 possible models. The specification curve plots the coefficient of interest (*Fatwa  $\times$  Muslim majority village*) and a 90 percent and 95 percent confidence interval for the different specification possibilities.

Appendix A.7 provides a detailed description of the four dimensions considered in the specification analysis and the resulting specification curve graph. The main specification is highlighted in blue. Overall, robust effects emerge across the different specifications. The null hypothesis of no effect can be rejected in 86 percent of the specifications at the 10 percent level. Exceptions rely mostly on two variations in alternative outcomes: first, burned area data with a larger space threshold as alternative outcome and second active fire data clustered using a 4Days  $\times$  2Pixels time-space window and a village buffer zone (to account for fire detections close to the village border). The insignificance may stem from the conservative clustering where many fire detections are grouped into one event and the

variation in the number of events across villages is reduced. Importantly, the specification curve shows that results are robust if the data is averaged to just two periods (before and after the fatwa) to address potential concerns regarding over-estimation of significance levels in a long time series (Bertrand, Duflo, & Mullainathan, 2004).

## 2.7 Discussion

In this study, I provide evidence suggesting that the MUI fatwa on land and forest burning resulted in a sizeable reduction of fire ignitions in Muslim majority villages. Furthermore, the negative relationship between the fatwa and agricultural burning as customary practice suggests that the decrease can be partially attributed to changes in communities' customary land practices. However, it is important to emphasise that the fatwa was not issued in isolation. Several government efforts, including regulations and initiatives such as the BRG, were launched simultaneously.

Given the available data, it cannot be determined how exactly the fatwa changed behaviour, i.e. whether it was through a genuine change in individual attitudes or perceived pressure from the community. However, considering my results with those of previous studies can provide some direction on how the fatwa may have changed behaviour. In a recent study, Edwards, Falcon, et al. (2020) find no effect of a collective PES scheme combined with a comprehensive programme on fire prevention in villages in Kalimantan. According to the programme design, collective payments were only issued if there were no observed fires. The authors speculate that the incentives from collective payment may have been insufficient to forgo the individual monetary benefit of land clearing through fire. It could be that the fatwa provided more individual incentives if individuals felt discomfort in engaging in activities they were instructed was *haram*. This may have led to an overall reduction in fire, although others still engaged in land burning behaviours and the village did not remain completely fire-free. A related study by Carmenta et al. (2020) evaluates the effectiveness of village-level interventions in preventing peat fires across 10 villages in Riau, Sumatra. These interventions were multi-faceted and included financial rewards, sanctions and raising health awareness. In line with results reported by Edwards, Falcon, et al. (2020), the authors find that financial rewards played a surprisingly small role. Instead, communities appeared to respond more strongly to sanctions. Similarly, the fear of engaging in a behaviour considered *haram* could partially explain the observed effect in this study. It could, however, also be the case that by establishing connections between environmental protection and Islamic scriptures, the fatwa succeeded in changing people's perceptions about land and forest burning, thereby motivating a change in

behaviour.

While it appears that the fatwa succeeded in reducing fire ignitions in the medium-term, it remains unclear whether the effect will continue. The larger positive coefficients for 2019 in the event study design could potentially indicate a fading effect of the fatwa. This could be explained by a possible decline in dissemination efforts combined with the need for continuous exposure to and reminders of the fatwa. It could also be that most people were already aware of the fatwa by 2019 but that repeated exposure could not stop the fading of the effect or induce behavioural change among those resistant to it. This could be the case if people initially reacted to the fatwa but then found that abstaining from fire use was too challenging economically. The increasing magnitude of the positive coefficients in 2019 could, however, also indicate that the fatwa is less effective under unfavourable conditions. In 2019, Indonesia experienced low levels of rainfall and an associated increase in fire risk. The findings of Santika et al. (2017) are in line with this possibility. The authors examine the performance of a community forest scheme in Kalimantan and Sumatra and find that drought years reduced the positive impact with respect to forest protection, especially on peatland and degraded land.

Although the fatwa may not have had a long-lasting effect on fire behaviours, the medium-term effect is noteworthy considering that the fatwa relates to a topic that is not historically associated with MUI. From the outset, it was unclear how much authority and influence MUI has over norms, attitudes and behavioural decisions related to land management practices. The results suggest that MUI fatwas on environmental issues can indeed have a measurable effect on peoples' behaviour. However, it should be noted that this fatwa was issued following a request by the Ministry of Environment and Forestry and is in line with government interests. Whether a fatwa on environmental protection can have similar effects if it is in opposition to government interests can not be determined but seems unlikely.

The heterogeneity of the fatwa concerning poverty levels highlights the importance of supporting villages in accessing alternative land clearing technologies that are equally economically feasible. The connection between poverty and deforestation is also highlighted in a study by Ferraro and Simorangkir (2020), which provides evidence that a national anti-poverty programme reduced deforestation in Indonesia. Combining value-based campaigns for the reduction of fire with concrete help towards finding alternatives for land burning could make religious support for conservation even more effective.

## 2.8 Conclusion

Forest fires persist in many parts of the world, including Indonesia, and currently constitute one of the most severe global environmental crises. A better understanding of how to reduce forest fires is thus essential. This study evaluates whether a religious environmental endorsement can increase pro-environmental behaviour. Following the latest extreme fire season in 2015, the Indonesian Muslim organisation MUI issued a fatwa in 2016, declaring land and forest burning as *haram* and thus forbidden according to Islam.

Building upon an 8-year panel dataset of monthly fire observations from 2012 to 2019, this study employs a matched DiD design to evaluate the success of this fatwa in reducing the number of fire ignitions observed at the village level. Muslim majority villages (treatment villages) and non-Muslim majority villages (comparison villages) were matched using the propensity score method. Results indicate that the fatwa was indeed successful in reducing fire events in Muslim majority villages by around 0.05 fire ignitions per month. Considering the average of 0.10 monthly fire ignitions in the matched comparison group during the post-fatwa period, this is a sizeable effect. The null results of a placebo analysis with logging induced primary forest deforestation as a placebo outcome increases confidence in a causal relationship between the fatwa and the reduction in fire ignitions. Furthermore, a comprehensive set of robustness checks in form of a specification curve shows that results are not driven by the specification chosen in the main analysis.

This study thus contributes empirical evidence regarding the potential impact of faith-based support on environmental conservation. The active request for the fatwa shows that the Indonesian Ministry of Forestry and Environment recognised this potential. Findings from this study have important implications for environmental policies and suggest that fire prevention efforts could benefit significantly from support by religious institutions and stakeholders, also in settings where a comprehensive set of government regulations and laws already exists. Assuming that the effect is partially caused by the moral authority of the religious institution, further research should investigate the applicability to other conservation contexts and other influential stakeholders that possess moral authority in the local context.

Finally, two important limitations of the study should be noted. First, this study does not allow for the identification of the mechanisms through which the fatwa influenced attitudes and behaviours. Whether the fatwa served to change attitudes towards land and forest burning or to increase social pressure and discomfort from engaging in an activity declared as *haram* remains speculated. Unfortunately, information on individual attitudes and behaviours is not available in the PODES data. Second, the role of the information disseminator or the information source remains unclear. Newspaper articles and qualita-

tive interviews suggest there is a great heterogeneity regarding the source of information on the fatwa. Some people learned about it from local preachers, some at village meetings and others from posters and media reports (including social media). Potentially, the source of information and the relationship with and trust towards the information source influences the effect of the fatwa. Future research on both the mechanisms and the roles of the information sources is required.

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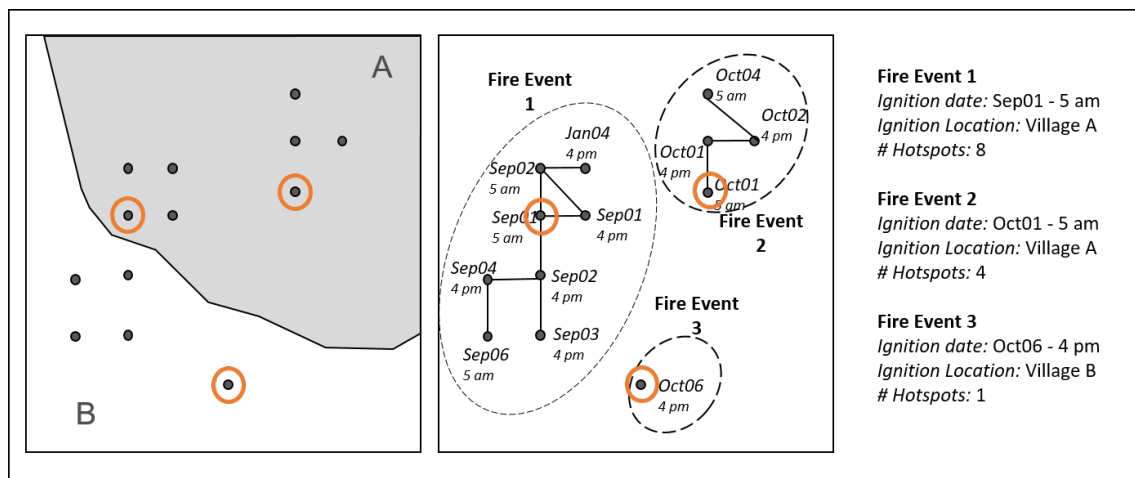
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## Appendix

### A.1. Additional information on the active fire data clustering

Active fire detections were clustered in three steps. First, I generated a spatial weight matrix to create a dyadic dataset on all relationships that fell within a pre-specified time-space window. Second, I used network analysis to cluster fire hotspots into fire events based on the dyadic dataset generated in step one (using Python package NetworkX). Third, I identified the earliest fire detection(s) within each fire event. This is considered the ignition source. Figure A.1.1 provides a visual description of the steps.



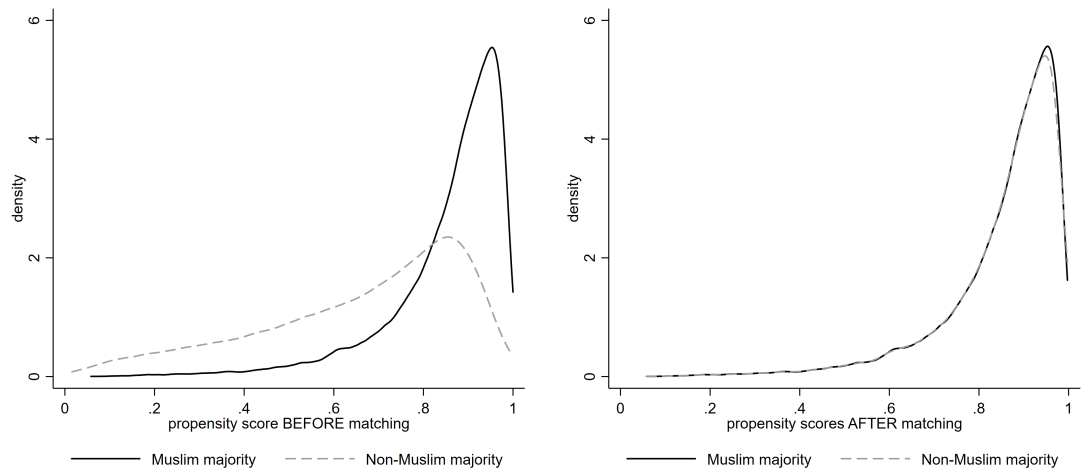
**Figure A.1.1:** Active fire clustering

Background information on pixel size in active fire data: The pixel size is not always 1 kilometre or 375 metres. Instead, the pixels at the edges of the satellite scan get bigger. Both the Modis and Viirs active fire products therefore also contain values for the ‘scan’ and ‘track’, which provide information regarding the actual resolution of the scanned pixel. The pixels are only exactly 1 x 1 kilometre or 375 x 375 metres at the exact vertical line from the satellite. To account for this in the clustering approach, I used a threshold of 500 metres for 1 pixel in the Viirs data. While this may lead to small distortions for some pixels at the outer edges of the scan, it does cover the majority of pixels. Similarly, I chose a threshold of 1.5 kilometres for the Modis data.

**Table A.2:** Overview different time-space windows

Data source	Time-space window	Count of observed village months with . . .						
		in total 29,265 villages x 96 months = 2,809,440 village months						
		0 fires	1 fire	2-3 fires	4-10 fires	11-50 fires	51-100 fire	100+ fires
Viirs	Hotspots	2,620,985	77,477	50,202	36,392	19,338	2,666	2,380
Viirs	2Days x 1Pixel	2,622,352	98,891	47,508	30,024	10,004	498	163
Viirs	2Days x 2Pixels	2,623,552	104,712	47,234	26,963	6,724	207	48
Viirs	4Days x 1Pixel	2,623,017	100,142	47,859	28,836	9,075	397	114
Viirs	4Days x 2Pixels	2,625,060	106,676	47,306	24,931	5,308	132	27
Modis	Hotspots	2,727,009	39,547	23,209	13,726	5,061	561	327
Modis	2Days x 1Pixel	2,727,102	41,213	22,952	13,119	4,399	425	230
Modis	2Days x 2Pixels	2,727,453	41,621	22,797	12,870	4,121	390	188
Modis	4Days x 1Pixel	2,727,232	41,346	22,972	13,018	4,259	405	208
Modis	4Days x 2Pixels	2,727,779	41,832	22,746	12,658	3,923	334	168
Burned Area	2Days x 1Pixel	2,792,702	4,470	4,067	4,808	2,984	293	116
Burned Area	2Days x 1Pixel	2,801,005	5,197	2,394	788	56	-	-





**Figure A.3:** Propensity scores before and after matching

## 2 CAN RELIGION HELP TO COMBAT FIRE?

**Table A.4:** Comparison of matching covariates before and after matching

	Unmatched			Matched (NN1)		
	Mean Treated	Mean Control	Stand. bias %	Mean Treated	Mean Control	Stand. bias %
Population density (People per km2)	279.77	118.25	48.1	269.99	300.42	-9.1
Poverty headcount as share	14.35	12.11	31.3	14.34	13.47	12.2
Agricultural burning is a customary practice (=1)	0.29	0.57	-57.3	0.30	0.29	1.2
Distance to the nearest police station (km)	8.34	16.93	-50.0	8.35	8.56	-1.2
Asphalt street to village (=1)	0.57	0.42	30.0	0.57	0.64	-13.4
Share of HH with electricity	0.92	0.74	65.0	0.92	0.92	-1.8
Wood is the main cooking fuel (=1)	0.38	0.66	-59.2	0.38	0.37	1.2
Peatland share	0.05	0.19	21.1	26.35	24.90	-1.9
Palm oil buffer share	0.21	0.14	0.5	1.77	1.66	-13.7
Primary forest share 2012	0.09	0.27	-101.0	0.05	0.06	-5.4
Mean monthly fire events 2002-2011	0.12	0.56	-5.8	0.12	0.12	0.1
Observations	23,997	5,268		23,821	3,801	
<i>Mean bias</i>			<i>41.0</i>			<i>5.2</i>
<i>Median bias</i>			<i>48.1</i>			<i>1.8</i>

*Note:* Information on villages characteristics is from PODES is from the 2014 Census. Agricultural burning is a customary practice, Asphalt street to village and Wood is the main cooking fuel are binary variables.

### A.5. Mosque share as an alternative treatment measure

Two aspects should be noted regarding *Mosque share* as an alternative treatment measure. First, the measure does not reflect the exact composition of faith within the village but rather provides a general indication. Consider a faith composition of 30 percent Christians and 70 percent Muslims. In a small village there may be one Church and one Mosque and in a bigger village one Church and two Mosques, resulting in a different *Mosque share* despite similar religious compositions between the villages. This also implies that small villages cannot be in all groups as, for example, a village with 200 inhabitants is unlikely to contain enough religious buildings for a Mosque share of 0.7. Furthermore, the number of churches is both a sign of the size of the Christian community and the acceptance of their religion by their Muslim counterparts/neighbours. Christians living in Muslim majority villages require not only a list of at least 90 members of their congregation but also a signature of agreement from 60 Muslim households and a permit from the local Religious Affairs office and the sub-district head (Marshall, 2018).

Second, there is considerable heterogeneity in fire-specific characteristics and pre-fatwa trends across groups. To increase comparability across groups, I restrict the sample to villages that commonly experience fires, i.e. the population of interest. The restricted sample comprises only villages with at least two yearly fires on average during the pre-study period (2002 - 2011). This improves the comparability across groups considerably.

Tables A.5.1 and A.5.2 provide descriptive statistics before and after restricting the sample (both samples include only villages with at least one reported religious building). While differences remain, they are considerably smaller in the restricted sample. Increased comparability also becomes evident when examining the fire trends provided by Figure A.5.1.

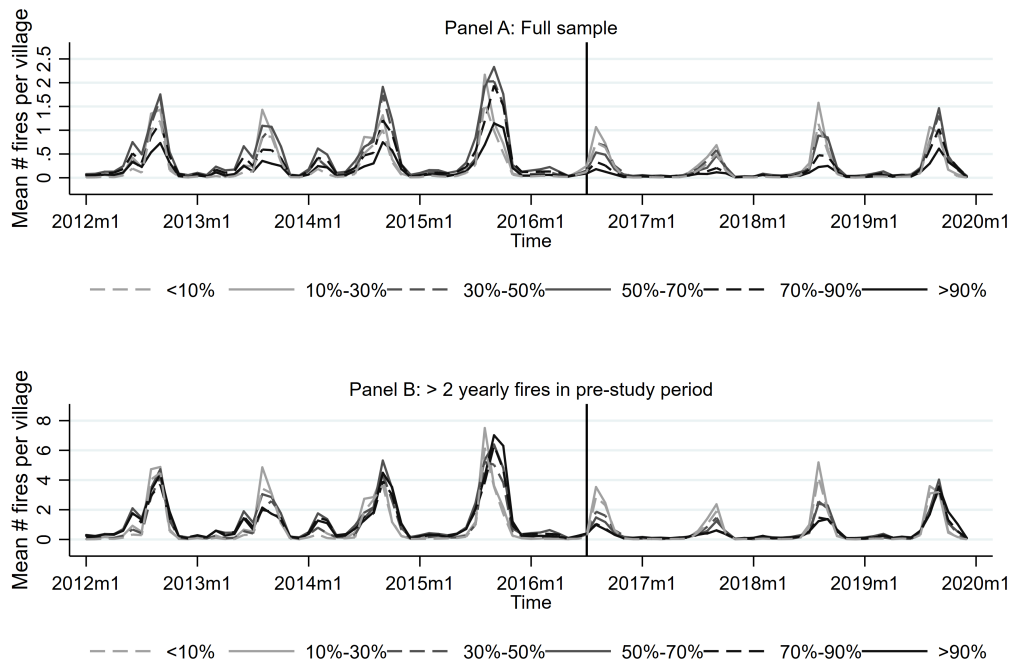
## 2 CAN RELIGION HELP TO COMBAT FIRE?

**Table A.5.1:** Descriptive statistics full sample by ‘Mosque share’ group

	<10%	10% - 30%	30% - 50%	50% - 70%	70% - 90%	>90%
	(N = 3,328)	(N =666 )	(N = 591 )	(N = 1,148 )	(N = 1,774 )	(N = 21,189 )
<i>Panel A: Socioeconomic characteristics</i>						
Population (in thousands)	1.03	1.98	2.08	2.52	2.93	1.63
Population density (People per km2)	109.06	137.17	166.02	206.30	206.29	288.54
Poverty headcount	13.30	10.39	9.61	9.34	10.22	14.90
Agricultural burning 2014 (=1)	0.56	0.53	0.59	0.49	0.29	0.29
Distance to police (km)	17.24	12.06	12.20	13.90	9.64	8.05
Asphalt street (=1)	0.39	0.58	0.54	0.41	0.40	0.59
Share of HH with electricity	0.71	0.85	0.87	0.87	0.95	0.91
Wood fuel (=1)	0.73	0.47	0.36	0.36	0.24	0.39
<i>Panel B: Fire characteristics</i>						
Mean monthly fire events 2002-2011	0.13	0.20	0.21	0.30	0.21	0.10
Any fire events 2002-2011 (=1)	0.54	0.59	0.67	0.69	0.66	0.47
Mean monthly fire events pre-Fatwa	0.22	0.32	0.37	0.48	0.34	0.21
Mean monthly fire events post-Fatwa	0.17	0.23	0.22	0.21	0.15	0.09
Any fire event pre-Fatwa (=1)	0.66	0.73	0.74	0.70	0.65	0.52
Any fire event post-Fatwa (=1)	0.57	0.61	0.64	0.61	0.55	0.41
<i>Panel C: Environmental characteristics</i>						
Rainfall (mm/month)	257.86	245.23	246.02	241.53	228.53	213.78
Temperature (monthly mean)	24.95	25.42	26.09	26.71	27.18	26.21
Wind (seconds/metre)	1.68	1.58	1.54	1.53	1.64	1.83
Peatland share	0.01	0.03	0.04	0.07	0.07	0.05
Palm oil buffer share	0.10	0.23	0.30	0.33	0.30	0.19
Primary forest share 2012	0.25	0.21	0.22	0.18	0.07	0.09
Annual primary forest deforestation 2010-2019 (ha)	21.45	31.84	40.12	56.89	25.04	14.86

**Table A.5.2:** Descriptive statistics sample > 2 yearly fires by ‘Mosque share’ group

	<10%	10% - 30%	30% - 50%	50% - 70%	70% - 90%	>90%
	(N = 3,328)	(N =666 )	(N = 591 )	(N = 1,148 )	(N = 1,774 )	(N = 21,189 )
<i>Panel A: Socioeconomic characteristics</i>						
Population (in thousands)	1.53	2.75	2.57	3.41	4.21	3.71
Population density (People per km2)	18.47	31.46	30.93	32.66	56.11	59.01
Poverty headcount	8.99	8.81	8.24	8.08	8.53	10.70
Agricultural burning 2014 (=1)	0.94	0.88	0.81	0.73	0.54	0.55
Distance to police (km)	27.69	18.49	16.85	20.59	13.21	13.80
Asphalt street (=1)	0.15	0.31	0.33	0.29	0.39	0.49
Share of HH with electricity	0.63	0.74	0.77	0.80	0.90	0.87
Wood fuel (=1)	0.77	0.56	0.45	0.48	0.29	0.35
<i>Panel B: Fire characteristics</i>						
Mean monthly fire events 2002-2011	0.53	0.73	0.57	0.90	0.75	0.69
Any fire events 2002-2011 (=1)	1.00	1.00	1.00	1.00	1.00	1.00
Mean monthly fire events pre-Fatwa	0.78	0.98	0.90	1.32	1.10	1.19
Mean monthly fire events post-Fatwa	0.61	0.71	0.54	0.58	0.45	0.47
Any fire event pre-Fatwa (=1)	1.00	1.00	0.99	1.00	0.99	1.00
Any fire event post-Fatwa (=1)	0.99	0.99	0.97	0.97	0.89	0.94
<i>Panel C: Environmental characteristics</i>						
Rainfall (mm/month)	289.51	279.23	266.90	251.35	233.45	224.97
Temperature (monthly mean)	26.66	26.99	27.07	27.26	27.43	27.25
Wind (seconds/metre)	1.38	1.47	1.46	1.45	1.56	1.53
Peatland share	0.03	0.07	0.10	0.13	0.16	0.18
Palm oil buffer share	0.21	0.31	0.31	0.33	0.33	0.32
Primary forest share 2012	0.36	0.26	0.28	0.27	0.15	0.17
Annual primary forest deforestation 2010-2019 (ha)	70.84	101.15	97.16	154.89	88.94	91.34



*Note:* Fire data is from the Viirs dataset. Fire detections were clustered into fire events using a 2Day x 2Pixels threshold (see Section 2.3).

**Figure A.5.1:** Fire trends before and after restricting the sample

**A.6. Non-formal Islamic school as an alternative treatment measure**

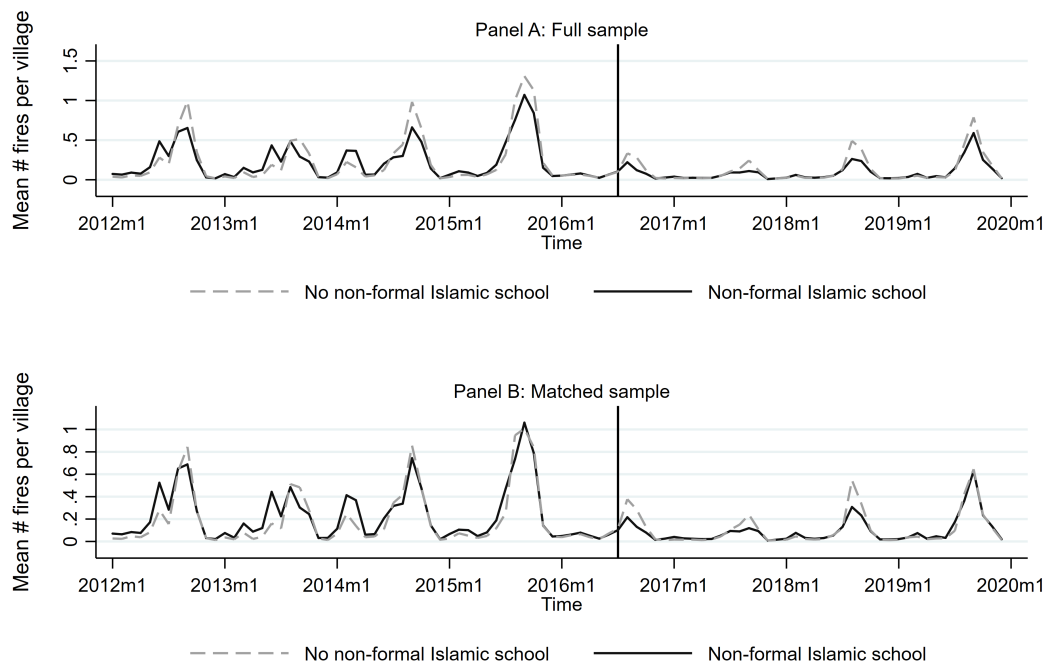
PODES provides information on the number of two types of schools that are not part of the formal education: Madrasah Diniyah (afternoon Islamic classes) and Pesantren (Islamic boarding schools). In some cases, Pesantren also encompass Madrasah Diniyahs. The use of a binary measure to denote whether there is at least one non-formal Islamic school avoids ‘double counting’ the same institution if it encompasses a Pesantren and one or more Madrasah Diniyahs. In contrast to NU and Muhammadiyah, MUI itself plays no significant role in the Indonesian education system. Pesantren in particular are largely affiliated with NU.

Table A.6.1 and Panel A of Figure A.6.1 show that there is considerable heterogeneity in fire-related village characteristics and pre-fatwa fire trends. Following the propensity score matching to reweigh the comparison group, village characteristics and pre-fatwa trends are more similar across the groups. Panel B of Figure A.6.1 provides evidence in support of parallel trends in the matched sample.

**Table A.6.1:** Descriptive statistics pre and post matching

	Unmatched		Matched (NN1)	
	Mean Treated	Mean Control	Mean Treated	Mean Control
Population density (People per km2)	325.49	219.49	343.23	221.35
Poverty headcount	13.19	14.27	12.91	12.49
Agricultural burning 2014 (=1)	0.25	0.38	0.26	0.35
Distance to police (km)	7.04	11.08	6.77	9.35
Asphalt street (=1)	0.62	0.51	0.63	0.61
Share of HH with electricity	0.94	0.86	0.94	0.92
Main cooking fuel wood (=1)	0.32	0.47	0.31	0.42
Peatland share	0.07	0.21	26.56	25.34
Palm oil buffer share	0.21	0.19	1.74	1.70
Primary forest share 2012	0.09	0.14	0.07	0.04
Mean monthly fire events 2002-2011	0.13	0.51	0.13	0.11
Observations	8,621	20,644	8,572	19,331
<i>Mean bias</i>		<i>21.4</i>		<i>14.0</i>
<i>Median bias</i>		<i>23.0</i>		<i>13.4</i>





*Note:* Fire data is from the Viirs dataset. Fire detections were clustered into fire events using a 2Day x 2Pixels threshold (see Section 2.3).

**Figure A.6.1:** Fire trends before and after matching

### A.7. Specification curve analysis

The following section provides details on four dimensions along which specifications can differ. First, to investigate the sensitivity of my results to measures of the fire outcomes, I compare three sources of fire data, an array of time-space windows for clustering fire detections into fire events and the use of buffer zones to account for fires occurring close to the village borders. Along with the Viirs active fire data, Modis active fire data and Modis burned area data are used as alternative sources of fire information. Furthermore, as noted in Section 2.3, there is not one time-space window that is known to be optimal for clustering fire detections into fire events. To exclude the possibility of the findings depending on my choice of the time-space window (2Days x 2Pixels), I consider several alternative time-space windows: no clustering (i.e. single fire hotspots), 2Days x 1Pixel, 4Days x 2Pixels and 4Days x 1Pixel. For the burned area data, I consider two time-space windows, namely, 2Days x 1Pixel and 2Days x 2Pixels. The different spatial resolutions of the data sources (i.e. 1000 metres for Modis active fire data, 375 metres for Viirs active fire data and 500 metres for Modis burned area data) further add to the variety of options considered. Finally, I employ buffer zones and assigned fire detections that occurred within 1 pixel of a village border to both villages. Considering that active fire detections represent the centre of a 375-metre pixel or a 1,000-metre pixel, they could be attributed to the wrong village if they occurred close to the border.

Second, to address potential concerns regarding over-estimation of significance levels in a long time series (Bertrand et al., 2004), I consider two additional panel lengths. The data is averaged to yearly data (8 years) and to just two time periods (pre- and post-fatwa).

Third, different matching options are compared. Instead of nearest neighbour with one match, I also consider nearest neighbour with two matches, two matches with calliper and kernel-based matching. Table A.7.1 provides an overview of the different options.

Fourth, I compare different options with regard to control variables. All specifications include time-fixed effects and village fixed effects and control for rainfall and average monthly wind speed. However, for the rainfall variable, I consider two options. The first option is the binary variable indicating whether rainfall was above (equal to one) or below (equal to zero) the 200 mm per month, which Sloan et al. (2017) identified as the critical threshold. Other studies confirmed the non-linear effect of rainfall but identified different thresholds (e.g. Sze, Jefferson, & Lee, 2019). For the monthly panel, I therefore include rainfall and rainfall squared as an alternative option to account for the non-linear relationship.

Additionally, I distinguish between three sets of additional controls (i) province-month

fixed effects and linear province time trends, (ii) province-month fixed effects and province-year fixed effects and (iii) all remaining controls: distance to police x post, BRG, yearly primary forest deforestation and the interaction between rainfall and villages' peatland share (including lagged rainfall). Alternative to the linear province time trend (i), I allow for province by year fixed effects (ii) to control for time-varying unobserved characteristics shared by villages in the same province. Province-by-year fixed effects account for policy changes at the province level, e.g. local conservation initiatives or province-specific laws and regulations. However, they also limit the comparison of villages to a within-province comparison, which is less suitable for villages in Sumatra where there is little variation in villages' main religion within most provinces.

Figure A.7.1 provides the specification curve depicting the estimated effect of the fatwa from a total of 2,082 specifications. The main specification is highlighted in blue. Overall, robust effects emerge across the different specifications. The null hypothesis of no effect can be rejected in 86 percent of the specifications at the 10 percent level. Exceptions rely mostly on burned area data as the outcome.

**Table A.7.1:** Comparison of matching options

Matching type	Total sample size	Number of treatment villages	Number of comparison villages	Mean stand. difference in covariates (%)	Median stand. difference in covariates (%)
Original sample	29,265	23,997	5,268	42.0	49.0
Nearest neighbour 1:1 with replacement	27,831	23,966	3,855	6.0	5.2
Nearest neighbour 1:2 with replacement	28,571	23,966	4,573	5.7	5.5
Caliper 1:2 with replacement	27,711	23,940	3,853	6.1	5.5
Kernel matching	29,248	23,966	5,262	5.4	4.6

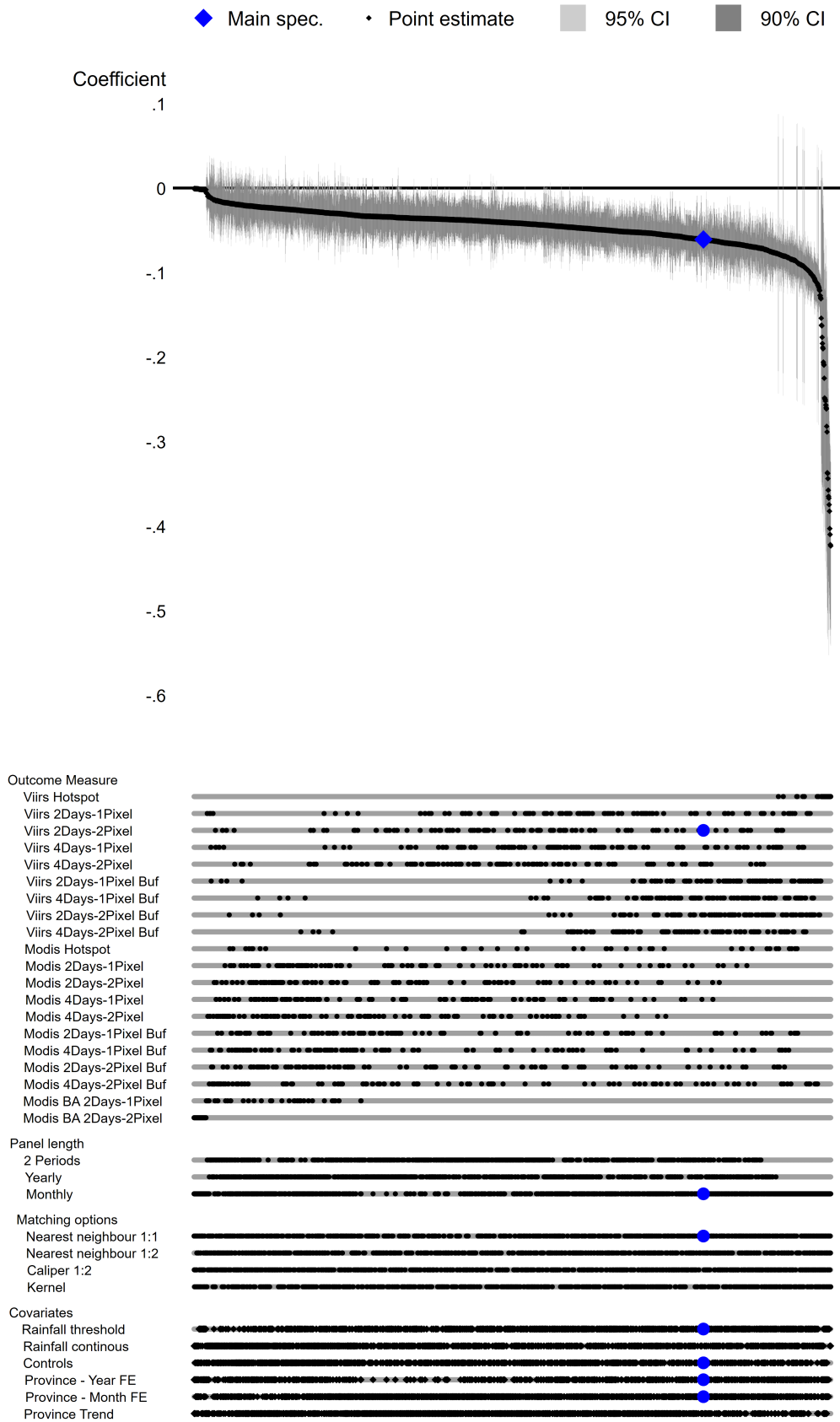


Figure A.7.1: Specification Curve





# **3 Can training enhance adoption, knowledge and perceptions of organic farming practices? Evidence from a randomised experiment in Indonesia**

*With Michael Grimm*

## **3.1 Introduction**

Over the past decades, farmers in Asia have widely adopted ‘Green Revolution’ type technologies and experienced rapid increases in productivity. However, several decades of intensively applying these technologies has come at environmental costs, i.e. degraded water and soil quality, as well as biodiversity loss (Hazell, 2009; IAASTD, 2009; IFAD, 2013; Lai, 2017). Furthermore, despite increases in productivity, farmers in Asia are still overrepresented in the lower-income segments and now additionally face the consequences of environmental degradation (IFAD, 2013). These concerns have led to increased interest in more sustainable farming systems such as organic farming. By abstaining from using chemical inputs and by promoting practices such as crop rotation and vegetative buffer zones, organic farming offers the potential to regenerate agricultural land and to counteract biodiversity loss (Jouzi et al., 2017; Seufert, 2012). Furthermore, several studies suggest that organic farming can also have positive effects on farmers’ livelihoods, mostly due to lower input costs, higher climate resilience, and the possibility of obtaining price premiums for organic products (Jouzi et al., 2017; Michler, Baylis, Arends-Kuenning, & Mazvimavi, 2019). However, despite policy efforts to promote organic farming, it remains a marginal activity in most Asian countries, as in other parts of the world. It is plausible to assume that widespread adoption of organic farming requires a better understanding of the drivers and barriers affecting its adoption, in line with previous studies highlighting the role of information as a driver for the adoption of agricultural technology (Foster &

Rosenzweig, 1995; Jack, 2011; Magruder, 2018). Providing farmers with information can increase knowledge of organic farming techniques, as well as awareness of problems associated with conventional agricultural techniques; both are prerequisites for subsequent adoption (Jones, 2002; Lee, 2005).

In this paper, we conduct a randomised controlled trial (RCT) to identify the effect of an organic farming training programme on farmers' use of organic inputs, as well as their knowledge and perceptions of organic farming. The experiment was implemented in two regions in Indonesia and encompassed 60 villages. Treatment and control groups were sampled from farmer groups that were invited to information sessions on organic farming. Subsequent to the baseline survey, half of the villages were randomly assigned to the treatment group while the other half formed the control group. The treatment group was further randomly split into three different treatment arms, which received different variants of the training programme, i.e.: (i) training only, (ii) the same training augmented by an awareness video on the negative impacts of chemical inputs on environmental and human health, and (iii) the same training augmented by a role-play to strengthen mutual support within farmer groups. Respondents in all treatment villages received an invitation to participate in the training, which was designed and delivered by the Indonesian non-governmental organization (NGO) Aliansi Organik Indonesia (AOI). The training consisted largely of participatory practical sessions, for example on how to produce organic fertiliser, but also included some classroom sessions on organic principles. AOI revisited all treatment villages around eight months after the training for a meeting to address questions that occurred since the training. Follow-up data was collected one year after the baseline survey and around eleven months after the training.

For decades, agricultural programmes have attempted to remedy information and skills constraints among farmers. Studies of such programmes have covered a wide range of extension programme types and agricultural technologies in different geographical and cultural contexts. These studies report mixed results for a variety of outcomes such as farmers' adoption of new technologies, knowledge, or improved use of chemical inputs (e.g. Fafchamps, Islam, Malek, & Pakrashi, 2020; Feder, Murgai, & Quizon, 2004; Kondylis, Mueller, & Zhu, 2017; Waddington et al., 2014). Many empirical studies report evidence for positive effects of extension programmes on the adoption of new technologies; however, the magnitude of the effects varies widely and farmers often adopt only a subset of the promoted technologies (e.g. Fafchamps et al., 2020; Hörner, Bouguen, Frölich, & Wollni, 2019; Larsen & Lilleør, 2014; Y. Pan, Smith, & Sulaiman, 2018; Takahashi, Mano, & Otsuka, 2019). For example, in a study of the impact of an agricultural extension programme targeting female farmers in Uganda, Y. Pan et al. (2018) found that the programme in-



creased the adoption of cultivation methods that require low upfront monetary investment but not the adoption of more capital intensive cultivation methods.

In addition to promoting the adoption of new technologies and improved use of inputs, extension programmes provide farmers with new information and skills, which may in turn increase their knowledge. However, evidence regarding knowledge improvements is mixed. Hörner et al. (2019), for example, found that training positively affected knowledge about integrated soil fertility management among farmers in Ethiopia. Guo, Jia, Huang, Kumar, and Burger (2015) observed that while farmer field schools improved knowledge among Chinese farmers, these improvements were heterogeneous with respect to knowledge area, age and gender. By contrast, extension programmes had no impact on knowledge among farmers in Mozambique who received direct training (Kondylis et al., 2017) or farmers in India who received access to mobile phone-based advisory services (Cole & Fernando, 2021), despite increasing the adoption of the promoted techniques in both settings.

Despite the variety of extension programmes studied, little is known about the impact of information provision on the adoption and knowledge of organic farming techniques. Organic farming has many features, which make it different from other technologies considered in previous studies. First, unlike many other ‘new’ technologies, organic farming is often considered more labour intensive than the practices farmers used in the first place. Second, the ultimate impact of organic farming on land productivity is uncertain and this may make farmers very reluctant to adopt it, given all they were taught about the importance of land productivity during the rollout of the Green Revolution. Third, farmers may be sceptical about the possibility of obtaining a price premium for organic products compared to conventionally grown products. Fourth, the short-term effects might be quite different from the long-term effects, as the regeneration of soils and consequent improvements in soil quality may take time. Fifth, it is sometimes claimed that training for organic practices is not even necessary, as it is the traditional way of farming. Sixth and lastly, compared to other ‘new’ technologies, it can be argued that organic farming justifies more public subsidies and other types of public support given its potentially strong positive externalities on the environment and health.

Existing studies on organic farming largely rely on observational data in developed countries (Burton, Rigby, & Young, 2003; Genius, Pantzios, & Tzouvelekas, 2006). Our contribution is to focus on an emerging country and to explore the effectiveness of providing information and hands-on training using an experimental design which allows to circumvent problems of self-selection and potentially confounding factors.<sup>1</sup> We adopt a

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<sup>1</sup>While earlier studies have been criticized to insufficiently address this selection bias (Feder et al., 2004; Larsen & Lilleør, 2014), recent studies have increasingly exploited RCTs to address this concern (e.g. Beaman & Dillon, 2018; Fafchamps et al., 2020; Guo et al., 2015; Hörner et al., 2019; Islam & Beg,

comprehensive approach that, in addition to studying treatment effects on knowledge and the use of organic inputs, also investigates how the training changed farmers' perceptions of organic farming. Until now, few studies have investigated the impact of information provision on farmers' perceptions.<sup>2</sup> Indonesia is an interesting case to study. Its exceptional agricultural growth in the second half of the twentieth century was largely based on the extensive use of chemical inputs strongly promoted by the government at the time. Yet, concerns about the adverse environmental impact of intensive chemical use are growing and over-application of chemical inputs has, for instance, long been identified as one cause of agricultural land degradation in Indonesia (Simatupang & Timmer, 2008). Today, policy makers encourage organic farming, also as a means to develop new export markets (David & Ardiansyah, 2017).

We find a statistically significant increase in the use of organic inputs, in particular self-produced non-manure organic fertiliser. Further, farmers in the treatment group were more likely to answer knowledge questions about organic farming correctly and to perceive organic farming as profitable and modern. Overall, our findings suggest that information constraints are a barrier to the adoption of organic farming as information provision increased the use of organic farming practices. However, as expected we cannot yet observe complete conversion to organic farming by farmers in the treatment group; rather it seems that a sizeable share of farmers in the treatment group has started to experiment with methods taught in the training while simultaneously continuing to use chemical inputs. Furthermore, we find no evidence for heterogeneous effects across the three treatment arms.

The rest of the paper is structured as follows. Section 3.2 describes the study context, sampling framework and experimental design. Section 3.3 details our estimation strategy and describes the sample. Section 3.4 presents our findings on the effects of the training. Section 3.5 discusses potential mechanisms linking the exposure to training and organic farming adoption. Section 3.6 concludes.

## 3.2 Context, Experimental Design and Data

Although its relative contribution to GDP is decreasing, the agricultural sector continues to provide an important source of employment and income for rural households in Indonesia. Dominated by small-scale farms, it constitutes the main source of employment

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2020; Kondylis et al., 2017; D. Pan, Kong, Zhang, & Ying, 2017; Rudolf, Romero, Asnawi, Irawan, & Wollni, 2020; Takahashi et al., 2019).

<sup>2</sup>Romero, Wollni, Rudolf, Asnawi, and Irawan (2019), for example, investigate the impact of information about biodiversity enrichment in oil palm plantations on farmers' perceptions in Indonesia.

for about half the country's rural labour force (BPS, 2018b). On Java, where this study was carried out, farm sizes are the smallest in Indonesia, with less than 0.5 hectares per household on average (BPS, 2014). Java is the most densely populated Indonesian island and population pressure further contributes to declining farm sizes. Most agricultural production is for self-consumption and income diversification towards non-farm income is common among agricultural households (BPS, 2014; OECD, 2012). Rice remains the most important staple food in Indonesia and Java is the country's leading rice producing area. Here, more than 50% of agricultural households, the majority of them smallholders, plant rice at least once a year (BPS, 2018a). Indonesia's political leaders promote rice self-sufficiency as being essential for achieving food security, a national goal that has remained at the top of the government agenda since independence in 1945. In the 1970s, rice yields increased significantly during the Green Revolution, due to the increased use of chemical inputs in combination with high-yielding rice varieties. The intensification of agriculture in the Green Revolution thereby made an important contribution to poverty reduction and food security in Indonesia (Schreer & Padmanabhan, 2020; Simatupang & Timmer, 2008).

However, while food security remains a central policy issue, concerns about the adverse environmental impact of intensive chemical input use are growing. Over-application of chemical inputs has, for instance, long been identified as one cause of agricultural land degradation in Indonesia (Simatupang & Timmer, 2008). According to the National Development Planning Agency BAPPENAS (2014), the over-application of the synthetic nitrogen fertiliser urea is causing widespread deterioration of agricultural land. Osorio, Abriningrum, Armas, and Firdaus (2011) report that smallholder rice farmers, who constitute the majority of rice farmers, apply on average twice as much urea per hectare than large-scale farmers, and more than officially recommended by the Indonesian Ministry of Agriculture. Further consequences of intensive and inappropriate chemical input use include biodiversity loss and water pollution. <sup>3</sup>

Organic farming, initially promoted by activists and NGOs, gained increasing popularity among Indonesian policy makers in the early 2000s as one alternative to chemical-intensive conventional farming. In 2001, the government launched the so-called 'GoOr-

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<sup>3</sup>Early on, in the 1970s and 80s, Indonesia experienced the negative consequences that agrochemical inputs induced biodiversity loss can have for agriculture. Following the excessive use of chemical pesticides, which destroyed both planthoppers and their natural predators, planthoppers were able to re-emerge in much larger numbers due to the absence of their natural predators. In response, a farmer-training programme on Integrated Pest Management (IPM) was widely implemented across Indonesia to minimize pesticide use among rice farmers. The training was delivered in the form of so-called farmer field schools, which utilise a participatory rather than top-down approach. Although the success of the IPM training is debated (Feder & Savastano, 2006), the participatory farmer field school approach remains a popular extension service tool.

ganic 2010' campaign, whose goal was for Indonesia to become the leading producer of organic food by 2010. Although this goal was not achieved, the campaign marked the beginning of political interest in organic farming and its institutionalisation in Indonesia. In 2003, the government introduced organic standards and since 2008, government budgets for fertiliser subsidies have included a share for organic fertiliser. In 2010, the government launched a second large-scale project named '1000 organic villages', which aims to introduce organic farming in 1000 villages across Indonesia. Furthermore, regional governments have launched their own programmes to support organic farming locally. For example, the Ministry of Agriculture in Kulon Progo District in Yogyakarta Province, one of our study locations, is currently collaborating with a national certification body to promote organic rice among farmers, with the aim of establishing 200 ha of certified organic rice in the district by 2020 (Katajogja, 2019). Alongside the government, NGOs remain active promoters of organic farming and private businesses are becoming increasingly involved. Yet, despite the political support, available statistics indicate that the share of land that is currently farmed organically is still below one percent (Lernoud & Willer, 2018).

Our field partner AOI is an umbrella organization and one of the largest NGOs in the organic farming context in Indonesia. Founded in 2002, today AOI is active in 18 Indonesian provinces to support local farmers and spread organic farming nationwide. AOI was fully involved in the design of the training intervention and ensured that it was tailored to the local context. A workshop held during the inception phase of the project in Yogyakarta in 2017 brought together a wide range of stakeholders, including farmers, activists, government officials and academics, whose different perspectives and expectations were integrated into the research design. Finally, the project is also intended to respond to broader knowledge gaps identified by the Bioeconomy International Initiative of the German Ministry of Education and Research.

#### *Sampling and Intervention*

The study was carried out in two regions on Java: Tasikmalaya District in West Java Province and Sleman, Bantul and Kulon Progo districts in Yogyakarta Province. These regions were selected based on the capacity of our field partner AOI, which has large institutional members in both regions who were capable of providing training to 300 farmers each.

For both regions we first compiled a list of all farmer groups that were not registered as organic, were focused on annual crops, and were not located on the construction site of the new Yogyakarta airport. In terms of size, we selected groups with more than 20 but fewer

than 200 members. A further requirement, to ensure adequate levels of participation in the information sessions, was that the total membership of selected groups in each village (Tasikmalaya) or subvillage (Yogyakarta) selected should be at least 60.<sup>4</sup> Applying these criteria, we obtained a sample of 1,392 farmer groups in 205 villages for Yogyakarta and of 1,412 farmer groups in 291 villages for Tasikmalaya. In total, we had to exclude around 64% of the farmer groups on the original list in Yogyakarta and around 13% of the groups in Tasikmalaya. Governmental data on farmer groups in Yogyakarta was more detailed and also provided information on the sub-village level and agricultural focus of farmer groups (e.g. annual crops or husbandry). This more detailed initial level of information in Yogyakarta led to a significantly higher share of dropped farmer groups. We then applied a three-stage random sampling design to select 1,200 respondents. In the first stage, we randomly selected 60 villages, 30 each from the 205 villages in Yogyakarta and the 291 villages in Tasikmalaya.<sup>5</sup> In the second stage, we randomly drew a minimum of one and a maximum of three farmer groups in each village until the total number of farmers in the selected farmer groups was equal to or larger than 60.<sup>6</sup>

After identifying the farmer groups, the members of the selected farmer groups were invited to an information session on organic farming, which was held in their village. These information sessions served two purposes: (1) to facilitate self-selection based on initial interest in organic farming and the willingness to participate in farmer group events; and (2) to collect contact details on prospective respondents. The information sessions were run by AOI. Enumerators and a field team from Germany were present at the sessions to assist with the collection of attendees' contact data. In the third sampling stage, 20 respondents from each village were randomly selected from among those attending the information session. If there were too few attendees at the information session, we asked the farmer group head to provide us with contact details of other farmer group members who did not attend the information session to make up the numbers to 20 respondents per village. To avoid bias during the baseline survey interview and biased nominations

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<sup>4</sup>Small and very large farmer groups were excluded as it would have been difficult to implement the intervention for very small or very large farmer groups. In advance of the survey, we visited each village (control and treatment) for an information session. The minimum group size was set taking into consideration that not every farmer in the selected farmer group would be interested in attending such an event. On the other hand, logistical reasons limited the possible size of these information sessions.

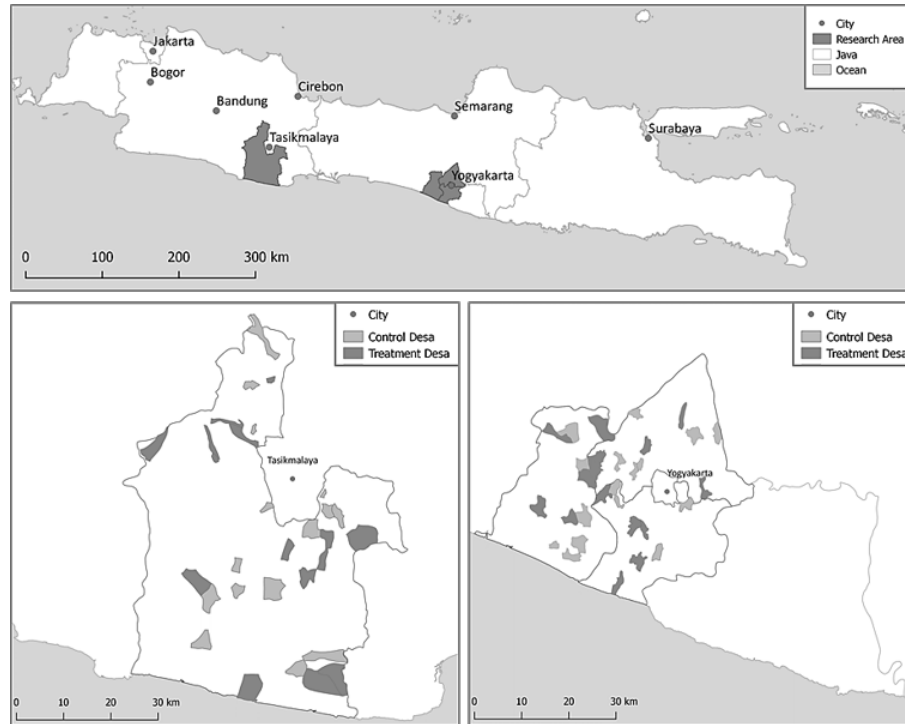
<sup>5</sup>Given that villages are, on average, larger in Yogyakarta than in Tasikmalaya and encompass more farmers we further randomised at the village level in Yogyakarta, i.e. one sub-village was randomly selected in each village. Selecting from villages in Yogyakarta might have led to the selection of farmer groups that are located far apart. This could have led to farmers having to travel longer distances to the training, which we tried to avoid in order to increase attendance.

<sup>6</sup>If the first drawn farmer group had 60 members or more, we only selected this one farmer group. Otherwise, we drew again. If first and second together counted at least 60 members, we stopped drawing. Otherwise, we drew a third farmer group.

of additional respondents by the farmer group head, we only informed farmers about the upcoming training after the baseline survey was completed in their village. Table A.3.1 in the Appendix provides descriptive statistics for farmers who did not attend the information session (non-attendees) by treatment status. The table shows that there seems to be no systematic difference between non-attendees from villages in the treatment group and those in the control group in terms of socio-demographic characteristics such as age, gender and education. There were some differences between the two groups with respect to beliefs about agricultural pollution, present bias and cultivated land size. However, in particular for the first two variables, this information is difficult for farmer group heads to assess and thus unlikely to be a consequence of biased nomination. Given that the unbalances occur for these variables and not for variables that are easier to assess, i.e. age, gender, education, we conclude that biased nominations by farmer group heads are unlikely to have occurred, first of all of course because the treatment status was unknown to the farmer group head at this stage.

The treatment was randomised at the village level and consisted of training on organic farming methods and principles. Farmers from groups in control villages did not receive any training. As baseline data was not available at the time of the randomisation, we used publicly available regional data for the stratification. Specifically, we stratified the sample according to urban and rural status and the reported size of agricultural land area per village. In Tasikmalaya, we used ‘travel distance to the district capital’ as an additional stratification criterion as this region is characterized by less developed infrastructure and long travel times within the district. The 30 treatment villages were further randomly assigned in equal shares to one of three treatment arms (i) training only, (ii) the same training augmented by a video on the negative impacts of chemical inputs to raise awareness for the potential health and environmental benefits of organic farming, and (iii) the same training augmented by a group exercise in form of a role-play to strengthen mutual support within farmer groups. As there were only ten villages per treatment arm, differences between arms would need to be large to be statistically detectable. However, given the low (or zero) cost nature of the training augmentations and our NGO partner’s interest in whether the impact of training could be increased by making small changes to the training design, we considered it worthwhile to add the treatment arms to the randomisation design. In our main analysis, however, we focus on the comparison between the control group and the overall treatment group. Figure 3.1 shows the location of the treatment and control villages.

After the baseline data collection, we invited the 20 interviewed farmers in each treatment village to participate in a three-day training on organic farming, with farmers receiv-



**Figure 3.1:** Research locations

ing seven hours of training per day. The training provided farmers with an introduction to organic farming, including information on organic farming principles and potential marketing channels. Particular emphasis was placed on practical activities such as testing soil health and making different organic fertilisers and pesticides. In the video session, the farmers were shown a video about the negative effects of using chemical inputs on the environment and human health, particularly the health of farmers who work with chemicals every day. The trainers then discussed the video content with the farmers. During the role-play session, the farmers were invited to participate in a role-play that was intended to highlight the importance of accountability of organic farmers towards their consumers. The role-play focused on the importance of recording the process of organic cultivation and working as a group. The training was designed by AOI in cooperation with the research team from Germany. AOI, together with its institutional members (local NGOs), delivered the training, which was held in the villages where the farmer groups were based to minimize travel time for respondents. The farmers received IDR 50,000 (around USD 3.5) for each day of the training (only if they attended) to cover any transport costs and to compensate them for potentially forgone earnings on that day. After the training, the farmers received a printed manual on organic farming. The training was rolled out at the end of March 2018 and completed in May 2018. On average, 17 farmers of the 20 invited farmers attended each training day.

*Data and descriptive statistics*

The data used in this study comes from two waves of survey data. Baseline data was collected between February and April 2018 and was directly followed by the training intervention. Regarding agricultural information, the baseline survey covered the most recently completed cropping cycle. Follow up data was collected between February and April 2019 and also covered the most recently completed cropping cycle.

From the 1,200 respondents interviewed at baseline, we successfully re-interviewed 1,149 respondents, representing an attrition rate of around 4%. The main causes of attrition were migration and health problems. The attrition rate was similar between the treatment and control group at 4.0% and 4.1% respectively. We further tested for attrition bias by regressing a binary variable for attrition status on treatment status and the regressors that appear in the main estimation equation. Table A.3.2 in the Appendix presents the regression results for the test for attrition bias; these show that treatment status is not statistically significantly different between attritted and returning respondents. For the other regressors, there is no statistically significant relationship with the attrition rate except for the regional dummy for Tasikmalaya and the dummy for ‘doing farming as main activity’, which are statistically significant at the 1% level and 10% level respectively. Given the low attrition rate and the absence of systematic differences between attritted and returning respondents, we conclude that attrition is unlikely to be a concern for our analysis. The remainder of our analysis is based on the 1,149 respondents who were interviewed at baseline and follow-up.

Table 3.1 presents summary baseline statistics by treatment status, including demographic information and agricultural production variables. The table shows that most respondents are male, with an average age of 54 years and eight years of completed education. While crop farming is the main economic activity for the majority of respondents, livelihood diversification is common. Around two-thirds of the sample engage in a secondary economic activity in addition to crop farming. Ownership of assets is mixed. An asset index calculated by summing up the assets owned by respondents’ households shows that households own, on average, 1.7 out of the following four assets: bike, motorcycle, car, fridge. However, about 12% of households own none of the listed assets; of these households, 94% are from Tasikmalaya. Respondents and their household members cultivate, on average, 0.3 hectares of land for crop production. This includes land for the production of staple crops such as rice, maize and cassava, as well as vegetables. The definition excludes, however, land for plantations such as trees or tee. The average proportion of land owned, rather than rented, is just over 60% for both treatment and control group. Around half of respondents own all the land they cultivate. However, only 35% of respon-



dents in Yogyakarta own all the land they cultivate, compared to 65% of respondents in Tasikmalaya. Rice is the dominant crop cultivated by farmers in our sample. Around 93% of respondents planted rice on at least one of their plots during the last cropping cycle. Furthermore, irrigation is widespread; most respondents (91%) cultivated at least one plot that was irrigated during the last cropping cycle.

**Table 3.1:** Descriptive statistics

	Control group mean	Treatment group mean	C-T
<i>Individual and household characteristics</i>			
Male	0.79	0.87	-0.08***
Age (in yrs.)	54.38	53.09	1.29
Muslim	0.96	0.97	-0.02
Schooling (in yrs.)	8.04	8.25	-0.21
Asset Index (bicycle, motorcycle, car, fridge)	1.69	1.77	-0.08
Farming is main activity	0.79	0.78	0.00
Farmers' decisions matter (perception)	0.59	0.56	0.02
Agr. env. Pollution is problematic (perception)	0.46	0.45	0.01
<i>Agricultural characteristics</i>			
Cultivated land (in ha)	0.30	0.41	-0.12***
Land ownership share	0.62	0.61	0.01
Rice (=1 if R planted rice)	0.94	0.91	0.03*
Irrigation (=1 if cultivated land is irrigated)	0.89	0.92	-0.03
<i>p</i> -value for joint orthogonality test		0.061	
<i>p</i> -value for joint orthogonality test (14 land outliers (>2ha) dropped)		0.493	

### Balance

We employ a joint orthogonality F-test to test for baseline balance between the control and the treatment group. Despite randomisation we obtain a p-value below 10% ( $p = 0.06$ ). Imbalances in gender composition and cultivated land sizes appear to drive the relatively low p-value. In fact, applying the joint-orthogonality test following the exclusion of cultivated land size outliers (i.e. cultivated land sizes  $> 2$  ha), results in a considerably higher p-value ( $p = 0.49$ ). Apart from cultivated land size and gender composition, characteristics are balanced between the control and treatments groups. Furthermore, values of other variables not used as controls in the main regression analysis are also well balanced between the control and the treatment groups and provide no evidence for structural differences between them. This allows us to conclude that there is no evidence of marked structural differences between the treatment and the control group that would invalidate the comparison of the two groups. To account for imbalance at baseline, our analyses control for baseline socioeconomic characteristics.

### Outcomes

We collected data on three types of outcomes variables: *application* of organic farming

inputs, *knowledge* about organic farming practices and *perceptions* of organic farming (see Table A.3.3 in the Appendix).

*Application* comprises three binary variables, namely (i) organic fertiliser other than manure, (ii) organic pesticide and (iii) processed manure. The value of each variable is equal to one if the respondent reported having applied the respective input during the last cropping cycle. We chose to focus on extensive margins since a large majority of respondents did not apply any of these technologies at baseline. Furthermore, we differentiate between ‘organic fertiliser other than manure’ and ‘processed manure’ to better capture the impact of the training. While processed manure (in contrast to unprocessed manure) is considered an organic fertiliser by the implementing NGO, the training focused on the production of organic fertiliser other than manure. At baseline, around one-third of the respondents reported having applied organic fertiliser or processed manure. Reported application rates for organic pesticide were much lower at around 8%. While there are differences between control and treatment group, these do not appear to be systematic; control group farmers used less organic fertiliser but more organic pesticide. In our regression design, we control for these baseline imbalances.

To measure *knowledge*, we asked respondents five questions focusing on the training content. For each question, we constructed a binary variable equal to one if the respondent answered correctly. Specifically, we asked respondents about (i) the existence of organic labels, (ii) land burning, (iii) processing of manure, (iv) the conversion period from conventional to organic farming, and (v) buffer zones between conventional and organic plots. At baseline, only a few respondents were aware of the existence of organic farming labels (22%). Around two-thirds knew that organic farmers should not burn land and should process manure before use. Knowledge levels at baseline appear to be similar across treatment and control group. However, we do not have baseline values for the last two knowledge questions; we therefore interpret treatment effects for these two questions with more caution.

To capture respondents’ *perceptions* of organic farming, we asked respondents (i) whether they perceive organic farming as ‘modern’ or ‘old-fashioned’, (ii) how they think the demand for organic products has developed over the past five years and (iii) how they think organic farming and conventional farming compare with respect to profitability. Again, we constructed binary variables for the three indicators, where values equal one if the respondent perceives organic farming as modern, believes that demand for organic products has increased over the past five years, and thinks organic farming is more profitable than conventional farming. At baseline, around 40% of respondents perceived organic farming as modern, while only around 19% thought that demand for organic products had in-

creased over the past five years. There are no notable baseline differences between control and treatment. Additionally, the analysis considers two measures of respondents' perceptions of the impacts of chemical inputs, namely whether they think it is true that chemical inputs have a negative effect on the environment and on farmers' health respectively.

### 3.3 Empirical Estimation

To estimate the impact of the training intervention, we focus on intent-to-treat (ITT) estimates; that is, simple comparisons of averages in treatment and comparison areas, averaged over all those farmers that had been invited to the training, whether they participated or not. On average, across the 30 treated villages, about 80% to 90% of all farmers invited to the training participated. Although the intervention was randomised and simple mean comparisons yield unbiased impact estimates, we include control variables observed at baseline to redress imbalances that showed up in the balance tests and to reduce the noise in the data to get more precise impact estimates. We estimate all specifications using a linear probability model.

Hence, the full regression model reads as follows:

$$Y_{iv} = \beta_0 + \beta_1 T_v + \gamma X'_{iv0} + \epsilon Y_{iv0} + \delta S' + u_{iv} \quad (3.1)$$

where  $Y_{iv}$  stands for the various outcome measures we are interested in observed for individual  $i$  of village  $v$ , including the application of organic fertiliser and pesticide, chemical input use as well as knowledge about and perceptions of organic farming. The variable  $T_v$  takes the value one if individual  $i$  lives in a treatment village. Hence the focus of interest of our analysis is the impact estimate  $\beta_1$ . The vector  $X'_{iv0}$  controls for baseline characteristics of the sampled individuals,  $S$  is a vector of randomisation strata.  $Y_{iv0}$  is the lagged outcome (at baseline). We include it for all outcomes for which it is contained in our data.  $u_{iv}$  stands for the error term. To account for within-village correlations of our variables, we cluster standard errors at the village level.

For outcomes for which we have baseline data, we first estimate the treatment effects including the lagged outcome as a control (ANCOVA specification). We then estimate treatment effects without the lagged outcome as a control for all our outcomes (POST specification). Controlling for the lagged outcome variables allows to account for minor imbalances in baseline outcomes and improves precision because lagged outcomes are often a strong predictor of outcomes at follow-up. We prefer the ANCOVA specification to a difference-in-difference specification because of the improvement in statistical power

(McKenzie, 2012). In the result section, we focus on the ANCOVA specification when possible and on the POST specification otherwise.

Since, as explained above, we implemented three variants of the treatment, i.e. just training (T), training and exposure to an awareness video (V) and training and participation in a role play (R), we also estimate Equation 3.1 with interaction effects that account for the additional intervention to see whether these can further increase the impact of the simple treatment. The specification then becomes:

$$Y_{iv} = \beta_0 + \beta_1 T_v + \beta_2 (T * V)_v + \beta_3 (T * R)_v + \gamma X'_{iv0} + \epsilon Y_{iv0} + \delta S' + u_{iv} \quad (3.2)$$

Given the small sample size, it is obvious that the statistical analysis will only detect relatively large differences in treatment effects between the normal training and the augmented training variants.

We also explore whether impacts depend on socio-economic characteristics, i.e. age, years of schooling, perception of agricultural pollution as problematic, cultivated land size, location, risk aversion and present bias (all measured at baseline).

Finally, we also estimate the Local Average Treatment Effect (LATE) using the invitation to the training as an instrument for actual participation, although we do not expect large differences between LATE and ITT estimates as training uptake was relatively high. Moreover, even if farmers did not participate in the training, they may have learned about the practices later through the day-to-day interaction with farmers who attended the training. Hence, it would be a strong assumption to consider a farmer of a treated farmer group as untreated because s/he did not attend the training.

#### *Multiple Hypothesis Testing*

Given that we test for a large number of outcomes, there is a higher probability of falsely rejecting the null hypothesis in some cases. We control for the potential false discovery of significant effects by correcting p-values for multiple hypothesis testing using the Benjamini-Hochberg method (Benjamini & Hochberg, 1995). Following Baird, McIntosh, and Özler (2019), who used q-values as derived in Anderson (2008), we present the corresponding q-values in our main tables.

#### *Randomisation Inference*

We further report p-values from randomisation inference tests for our main results. The randomisation inference based p-values are derived by randomly assigning treatment status within the strata and estimating a distribution of the parameter of interest (based on 5,000 permutations). Randomisation inference tests the robustness of our results since

it relies entirely on randomisation without making any distributional assumptions about the test statistics (Heß, 2017).

## 3.4 Results

In this section, we first examine whether training changed farming input-related behaviour, knowledge about organic farming and perceptions of organic farming. Comparing the coefficients from the ANCOVA and the POST models, we find that these specifications generate very similar results in terms of coefficient size, sign and significance level. This lends additional robustness to our results from the POST specifications. In the second step, we explore whether treatment arms matter before looking at heterogeneity in treatment effects based on the observed characteristics. Lastly, we perform robustness checks for the main results.

### *Application*

Increasing the application of organic practices was the main objective of the training. We thus begin by examining whether training led to behavioural change, i.e. an increase in the use of organic inputs and a decrease in the use of chemical inputs. Table 3.2 presents the results.

Cols. (1) and (4) show the intention-to-treat effect (ITT) on farmers' use of organic fertiliser and organic pesticide. Farmers assigned to the treatment group are on average 13 percentage points more likely to use organic fertiliser and 8 percentage points more likely to use organic pesticide. In the ANCOVA model, both treatment effects are significant at the 1% level. Furthermore, treatment effects are robust to controlling for the number of false discoveries (FDR adjustment) and remain significant at the 1% and the 5% significance level, respectively.

In the follow-up survey, we further asked farmers whether they produced the respective organic input themselves or whether they bought it. Cols. (2) and (4) show the ITT effect on the probability that farmers produced at least part of the organic input, while Cols. (3) and (6) show the effect on the probability that farmers purchased at least part of it. We find that the estimated effects are considerably higher and, in the case of organic fertiliser, only statistically significant for self-produced organic inputs. This indicates that encouragement and instructions for self-production seem to drive the positive effect on organic fertiliser and organic pesticide use. However, adjusting for the FDR, we can no longer reject the null hypothesis of no impact on the use of self-produced fertiliser. We further examine the impact on the use of processed manure. While the estimated

coefficient is positive and suggests an increase in the probability to use processed manure by 5 percentage points, the effect is only significant at the 10% level in the ANCOVA model and is not robust to the FDR adjustment.

**Table 3.2:** ITT effects on input application (OLS estimation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Organic fertilizer	Organic fertilizer <i>produced</i>	Organic fertilizer <i>purchased</i>	Organic pesticide	Organic pesticide <i>produced</i>	Organic pesticide <i>purchased</i>	Processed manure	No chemical fertilizer	No chemical pesticide
<b>ANCOVA</b>	0.126*** (0.000)			0.091*** (0.010)			0.058* (0.094)	0.001 (0.933)	0.093* (0.057)
[q-value]	[0.001]			[0.030]			[0.123]	[0.933]	[0.103]
{p-value RI}	{0.000}			{0.005}			{0.140}	{0.943}	{0.082}
<b>POST</b>	0.166*** (0.000)	0.139*** (0.000)	0.051 (0.131)	0.075** (0.033)	0.062* (0.052)	0.027* (0.095)	0.051 (0.183)	0.005 (0.765)	0.102* (0.064)
[q-value]	[0.001]	[0.001]	[0.169]	[0.099]	[0.115]	[0.143]	[0.206]	[0.766]	[0.115]
{p-value RI}	{0.000}	{0.000}	{0.149}	{0.030}	{0.029}	{0.107}	{0.227}	{0.778}	{0.088}
Control mean (follow up)	0.27	0.14	0.15	0.07	0.02	0.03	0.33	0.05	0.40
Strata	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N (ANCOVA)	1,146			1,142			1,146	1,146	1,146
N (POST)	1,149	1,107	1,107	1,149	1,145	1,145	1,149	1,150	1,150
R-squared (ANCOVA)	0.301			0.061			0.108	0.072	0.120
R-squared (POST)	0.078	0.022	0.077	0.069	0.056	0.120	0.046	0.034	0.056

*Note:* \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses. Multiple hypothesis adjusted q-values in square brackets. For the ANCOVA model, q-values are based on the rank relative to the naive p-values from the POST model for the outcomes for which there is no lagged outcome. P-values from randomization inference in curly brackets.

Given the positive impact of treatment assignment on the probability of using organic inputs, one might expect a decrease in the use of chemical inputs if organic inputs are perceived as a substitute. Considering the substantial effect on organic fertiliser use, this effect should be particularly strong for chemical fertiliser. However, we find no significant impact of training on the use of chemical fertiliser (Col. 8).<sup>7</sup> Instead, chemical fertiliser use remains high in both the treatment and the control group. From the results using the ANCOVA model, we find that farmers assigned to the treatment group are 9 percentage points more likely to abstain from using chemical pesticide (Col. 9). However, results are not robust to the FDR adjustment. In summary, our results provide evidence for increased experimentation with and adoption of the methods taught during the training among farmers assigned to the treatment group. It should be noted that the absence of an impact on chemical input use, even if somewhat surprising, is an indication that social desirability bias is unlikely to be a problem for this set of outcomes. Otherwise, we would expect farmers to report not just an increase in the use of organic inputs, but also

<sup>7</sup>We also find no effect if we use ‘money spent on fertiliser’ as outcome variable (and similarly no effect for ‘money spent on chemical pesticide’).

a reduction in the use of chemical inputs.

### *Knowledge*

Measuring knowledge serves two purposes. First, it allows assessment of knowledge gains. Second, it allows measurement of the training impact in a way that is not prone to a bias arising from strategic answers by respondents, i.e. if they just report what they think interviewers want to hear without understanding the answers they give.

Table 3.3 shows the results. As shown in Col. (1), there is a substantial increase in knowledge about the existence of organic labelling among farmers in the treatment group. Only 24% of farmers in the control group reported knowing about the existence of labelling compared to 46% in the treatment group. However, closer examination reveals that only a few farmers, in both the treatment and the control group, could name specific labels (less than 1% in the control group and around 2% in the treatment group). Cols. (2-4) show the training effect on questions that test farmers' knowledge about prohibited and required practices in organic farming. Farmers assigned to the treatment group were around 14 percentage points more likely to know about the prohibition of land burning, around 7 percentage points more likely to know about the requirement to process manure before application and, finally, 20 percentage points more likely to know about the requirement for a buffer zone between organically farmed land and conventionally farmed land.<sup>8</sup> Furthermore, the training caused a 16 percentage point increase in the probability that respondents knew that the conversion from conventional to organic farming requires some time. This is important as realistic expectations about conversion times prevent disappointment after initial adoption and subsequent disadoption. Effects on all knowledge outcomes are robust to the FDR adjustment. Overall, farmers in the treatment group answered 0.76 more questions (out of five) correctly compared to farmers in the control group who answered, on average, 2.7 questions correctly. Thus, the positive effects we find for knowledge further strengthen the robustness of our findings for the application of organic practices.

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<sup>8</sup>Farmers who correctly answered the questions on land burning and manure processing, were further asked open-ended questions requesting them to explain why land burning is seen as negative and how one can assess whether manure is ready. Enumerators were instructed on the right answer and to code respondents' answers as correct or wrong. We find that, conditional on answering the first question correctly, farmers assigned to the treatment group are not more or less likely to answer the follow up open-ended question correctly. While this indicates that the training was not successful in teaching everyone a better understanding, it also provides suggestive against strategic answering (since in this case the share of correct answers should be substantially lower in the treatment group).

**Table 3.3:** ITT effects on knowledge (OLS estimation)

	(1) Labels	(2) No land burning	(3) Manure processing	(4) Conversion period	(5) Buffer zone	(6) Knowledge index
<b>ANCOVA</b>	0.200*** (0.000)	0.138*** (0.000)	0.067** (0.038)			
[q-value]	[0.001]	[0.001]	[0.038]			
{p-value RI}	{0.000}	{0.001}	{0.073}			
<b>POST</b>	0.195*** (0.000)	0.136*** (0.000)	0.065** (0.047)	0.161*** (0.000)	0.202*** (0.000)	0.759*** (0.000)
[q-value]	[0.001]	[0.001]	[0.048]	[0.001]	[0.001]	
{p-value RI}	{0.000}	{0.001}	{0.082}	{0.000}	{0.000}	
Control mean (follow up)	0.24	0.74	0.77	0.48	0.49	2.71
Strata	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N (ANCOVA)	1,150	1,149	1,150			
N (POST)	1,150	1,150	1,150	1,150	1,150	1,150
R-squared (ANCOVA)						
R-squared (POST)	0.172	0.063	0.045	0.124	0.105	0.212

*Note:* \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses. Multiple hypothesis adjusted q-values in square brackets. For the ANCOVA model, q-values are based on the rank relative to the naive p-values from the POST model for the outcomes for which there is no lagged outcome. P-values from randomization inference in curly brackets.

### Perceptions

Table 3.4 presents the impact of the training intervention on farmers' perceptions of organic farming. The results indicate that the training positively affected farmers' perceptions of organic farming and strengthened their awareness of the negative effects associated with conventional farming. The estimated coefficients are statistically significant and robust to the FDR adjustment. Specifically, we find that farmers assigned to the treatment group were 8 percentage points more likely to perceive organic farming as a 'modern' rather than an 'old fashioned' technology. Further, farmers in the treatment group were 14 percentage points more likely to think (rightly) that within Indonesia, demand for organic products has increased in the past five years. The training also increased the probability that farmers perceive organic farming as more profitable compared to conventional farming. The probability that farmers think that chemical inputs negatively affect the environment and farmers' health increased by 6 and 7 percentage points respectively.

### Treatment Arms

So far, we have considered the treatment group as a single group. However, as described previously, the full design consists of three treatment arms: just training (T), training augmented by exposure to an awareness video (V) and training augmented by participation in a role-play (R). Given the similarity between the three treatment arms



**Table 3.4:** ITT effects on perceptions (OLS estimation)

	(1) Modern	(2) Demand increased	(3) More profitable	(4) Chemicals: neg. for env.	(5) Chemicals: neg. for health
<b>ANCOVA</b>	0.082** (0.015)	0.143*** (0.000)			
[q-value]	[0.020]	[0.001]			
{p-value RI}	{0.029}	{0.001}			
<b>POST</b>	0.079** (0.023)	0.143*** (0.000)	0.115*** (0.001)	0.064** (0.046)	0.067*** (0.005)
[q-value]	[0.030]	[0.001]	[0.000]	[0.047]	[0.009]
{p-value RI}	{0.042}	{0.001}	{0.003}	{0.079}	{0.011}
Control mean (follow up)	0.37	0.37	0.52	0.71	0.76
Strata	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N (ANCOVA)	1,150	1,150	1,150	1,150	1,150
N (POST)	1,150	1,150	1,150	1,150	1,150
R-squared (ANCOVA)	0.117	0.113			
R-squared (POST)	0.111	0.113	0.094	0.105	0.087

*Note:* \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses. Multiple hypothesis adjusted q-values in square brackets. For the ANCOVA model, q-values are based on the rank relative to the naive p-values from the POST model for the outcomes for which there is no lagged outcome. P-values from randomization inference in curly brackets.

and the loss in statistical power from analysing the treatment group separately, we would not expect substantial differences between the impacts of the respective treatment arms. Yet, the awareness video and the role-play represent very low-cost augmentations to the training and even small differences would thus be of interest to policy makers. Tables A.3.4 - A.3.6 report the results for the analysis of differential impacts across treatment arms. The interaction effects between *Training* and *Video* or *Role-play* indicate whether the respective augmentation was significantly different from the training-only treatment. We further test for the equality of the two interaction coefficients.

Overall, our results indicate that the three training variants had generally similar impacts. For the adoption outcomes (Table A.3.4), we cannot reject the null hypothesis that the two augmentations have the same impact as training-only treatment. Furthermore, the differences between the estimated interaction coefficients are not statistically significant at the 10% significance level for all outcomes. Among the knowledge outcomes (Table A.3.5), there is only one outcome, i.e. knowledge about the requirement to process manure before application, for which one treatment arm is significantly different from the other two. The coefficient of the interaction term *Training\*Role-play* is positive and statistically significant at the 5% significance level and the difference between the estimated interaction terms is statistically significant at the 10% level. For the perception outcomes

(Table A.3.6), we find that farmers assigned to the video treatment were more likely to think that chemicals negatively affect the environment (Col. 4) and farmers' health (Col. 5) compared to farmers assigned to the training-only group. However, employing the Wald test for equality of coefficients, we cannot reject the null hypothesis of no difference between the video and the role-play treatment arm at the 10% significance level.

Summarising, we cannot find robust evidence that the training effect can be enhanced by no/ low-cost augmentations such as a video treatment or a role-play. However, when interpreting these results, one should keep in mind the limited size of the subsamples and hence the limited power as well as that both augmentations only took around two additional hours within a three-day training programme. Hence, our results can say very little about what more extensive augmentations to the training programme could achieve.

#### *Heterogeneity in Treatment Impact*

Policy makers and other stakeholders are often interested in the heterogeneity in treatment effects, i.e. whether some sub-populations are more responsive to the training than others are. In the following, we examine heterogeneity in treatment effects based on the observed characteristics we specified in the Pre-Analysis Plan.<sup>9</sup> Specifically, we examine heterogeneity in treatment effects for farmers' age, education, awareness of agricultural environmental pollution, risk attitude, land size, and the research location (Tasikmalaya district or Yogyakarta province) – all of which were measured at baseline. Tables A.3.7 - A.3.9 in the Appendix present the results.

Table A.3.7 shows heterogeneity in impacts of training on the application of organic practices. We find suggestive evidence for heterogeneity in impacts with respect to the research location. Yet, these results are not robust to the FDR adjustment, likely because of a loss in statistical power due to the large set of outcomes. Findings should, therefore, be interpreted with caution. Positive interactions between treatment assignment and the region dummy Tasikmalaya indicate that the training was more successful in raising adoption of organic fertiliser and decreasing chemical input use in Tasikmalaya compared to Yogyakarta.

Table A.3.8 shows heterogeneity in impacts for the knowledge outcomes. After adjustment for the FDR, we find only one significant interaction, namely between treatment assignment and awareness for agricultural pollution; see Col. (2), which reports impacts on the knowledge about the prohibition to burn land. As land burning is associated with air pollution, this finding might be explained by the initially higher knowledge about the negative effects of land burning among those farmers who reported awareness for

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<sup>9</sup>Registered in the AEA RCT registry: ID AEARCTR-0003840.

agricultural pollution at baseline.

Finally, Table A.3.9 reports treatment heterogeneity for the perception outcomes with respect to farmers' age, education, awareness for agricultural environmental pollution and cultivated land size. We find FDR-robust heterogeneity in impacts for two outcomes: the perception that chemicals can have negative environmental effects (Col. 4) and the perception that chemical inputs can have negative health effects (Col. 5). For the first outcome, significant and negative interactions between treatment assignment and age as well as education suggest that the training impact decreases with farmers' age and education. However, we do not find similar effects for other perception outcomes. For both outcomes related to the perceptions regarding chemical inputs, we further find negative and significant interactions between treatment assignment and cultivated land size. These results suggest that the training had a lower impact on farmers who cultivated more land.

#### *Local Average Treatment Effect*

Tables A.3.10-A.3.12 in the Appendix present the LATE estimates across the main outcomes when the invitation to the training is used as an IV for training attendance. Overall, the LATE estimates are slightly higher in magnitude than the ITT estimates. However, this difference is very small. For example, for the outcome 'use of organic fertiliser' we find an ITT effect of 12.6 percentage points compared to a LATE effect of 14 percentage points. The similarity between the LATE estimates and the ITT estimates can be explained by the high compliance, i.e. the high training attendance rate.

#### *Potential Spillover Effects*

A key assumption for randomisation to provide unbiased results is that potential outcomes are independent of the treatment status of other villages. Spillovers of the training impact on other villages in our sample would violate this assumption and could cause biased estimates of the treatment effect. Given the size of the villages, which often comprise several farmer groups, and that training participants reported they mainly discussed the training content with other members of their farmer group or their own family, we considered spillover effects to other farmer groups to be unlikely. Nevertheless, we tested for potential spillover effects. To do so, we constructed a measure of the number of treatment villages within a radius of 5 kilometres of each villages. We then regressed the respective outcomes on this measure (while controlling for own treatment status). Tables A.3.13 - A.3.15 in the Appendix present the results. The number of treatment villages within 5 kilometres has no systematic statistically significant effect on input application, knowledge or perception. This result also does not change if this radius is increased to 8

kilometres.<sup>10</sup>

## 3.5 Discussion

In this section, we summarise our main findings, relate them to the literature and elaborate on the underlying mechanisms linking the exposure to training and the use of organic farming practices, which, as we explained in the Introduction, entails a number of additional challenges compared to other technologies for which similar studies have been carried out. The main behavioural hypothesis we tested is that removing information barriers would lead to an increased use of organic farming inputs. Eleven months after the training was implemented, we do indeed find causal evidence that the training increased the use of self-produced organic fertiliser and organic pesticide. Our ITT effects are similar in magnitude to those found by Hörner et al. (2019) for the impact of an Integrated Soil Fertiliser Management programme on the adoption of individual practices among smallholders in Ethiopia (9 – 22 percentage points). They are also comparable to those found by Kondylis et al. (2017) for the impact of an Sustainable Land Management training among (lead) farmers in Mozambique (17.6 percentage points).

We expect that the ‘success’ of the training was likely due to a combination of factors. Firstly, positive changes in knowledge and perceptions brought about by the training increased farmers’ propensity to experiment with organic inputs and to adopt organic inputs in response to the training. This effect is also suggested in reports of previous similar studies focusing on sustainable agricultural technologies (Hörner et al., 2019; Kondylis et al., 2017; Romero et al., 2019). In our study, the training raised knowledge levels considerably, and this effect is in line with those reported by some previous studies (Fabregas, Kremer, & Schilbach, 2019; Hörner et al., 2019). However, other studies report that information provision may fail to increase knowledge even if it leads to increased adoption of the promoted practice (Cole & Fernando, 2021; Kondylis et al., 2017). As outlined above, in our study, farmers received information on both how to adopt organic practices and on why they should do so. Regarding the latter, we find that the training led to a more positive perception of the profitability of organic products and increased awareness of the negative effects that come with chemical inputs. To date, few studies have investigated the impact of information provision on perceptions and their influence on the adoption of agricultural technologies. A notable exception is a randomised study by Romero et al. (2019), who found that the provision of information on biodiversity enrich-

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<sup>10</sup>In Tasikmalaya, the average number of treatment villages in a radius of 5 km is 1.33 and 1.15 for treatment and control villages respectively. In Yogyakarta, the average number of treatment villages in a radius of 5 km is 2.4 and 1.73 for treatment and control villages respectively.

ment to smallholders cultivating oil palm plantations in Indonesia significantly affected their perceptions of the benefits of diversification. Very similarly, we find that training had a positive impact on farmers' perceptions of organic farming and their awareness of the potential negative effects of intensive use of chemical inputs. While we expect that changes in knowledge and perceptions contributed to the observed behavioural change, our study does not provide conclusive evidence for this effect – at least in the short run. This is partly due to the type of knowledge questions in our survey, which tested mainly for formal knowledge (e.g. regarding labels) rather than practical knowledge (e.g. how to produce organic fertiliser). Unfortunately, our data do not permit us to determine the temporal sequence of changes in knowledge, perceptions, experimentation and ultimately adoption.

A second possible mechanism through which the training may have influenced behaviour is through an encouragement (or persuasion) effect. Endorsement of organic farming by an external trainer may have acted as a form of 'expert validation'. This is in line with the evidence from qualitative interviews that we conducted with farmers who participated in our training. A farmer in Tasikmalaya, for example, explained his renewed use of organic fertiliser made of banana trees as follows: *'So it has actually already been there for centuries. But after the training, I got reminded, I got confirmation in the sense that it is actually correct, that it has a good effect on my crops. Therefore, I am using it again. But I already tried it a long time ago actually. From my father, when I was a kid, I saw that he used that. But I wasn't sure whether it was good or not.'* This kind of effect might explain results reported by some other studies, i.e. that information provision increases the use of the promoted technology but has no effect on knowledge levels (Cole & Fernando, 2021; Kondylis et al., 2017).

Thirdly, the group setting of the training may have reinforced the training effect. We selected a maximum of three farmer groups per village to ensure that members from the same farmer group jointly participated in the training. This may have benefited farmers who prefer to experiment with new technologies in a group rather than by themselves. Experimenting in groups allows farmers to draw on their peers' knowledge and moral support. Indeed, when asked at follow-up, 49% of new users of organic fertiliser and 72% of new users of organic pesticide in the treatment group reported having practised techniques taught in the training course with other attendees. Furthermore, the participation of several members of one farmer group (including, in most cases, the head of the group) may have helped amplify positive perceptions of organic farming among other group members. Studying the spatial patterns of organic farming in Honduras, Wollni and Andersson (2014) confirm the importance of social conformity. The authors find that

perceived approval for organic farming by neighbours increases the likelihood of engaging in organic farming.

While we find a positive impact of the exposure to the training on rates of experimentation with and adoption of organic inputs, farmers differed in their responsiveness to the training. We attempted to identify factors which may explain the heterogeneous training effect but found only limited evidence for links between different responses to the training and differences in age, education or risk aversion. Evidence from previous studies is also mixed and there appears to be no clear pattern in the adoption of agricultural conservation technologies with respect to factors such as age, gender or education (Knowler & Bradshaw, 2007). Some studies suggest that environmental concerns motivate farmers to convert to organic farming. However these findings, for example from Ireland (Läpple & Rensburg, 2011) and Ghana (Kleemann, Abdulai, & Buss, 2014), are not confirmed by a study in Honduras (Wollni & Andersson, 2014). In line with this study from Honduras, in our study, prior awareness of agricultural pollution (measured at baseline) was not associated with a significant difference in the effect of the training. Moreover, there is no evidence that the effect of the training was stronger among farmers who sell their products on the market, since farmers who produce only for their own consumption responded equally strong to the training. This is interesting given that price premiums and high profitability are frequently suggested as the main motivations for engaging in organic farming. In contrast, the most frequently stated motivation for organic fertiliser use at follow-up was its beneficial effects on soil quality.

Finally, the results raise the question of why the training did not translate into a reduction in chemical fertiliser use and only in a small reduction in pesticide use. An explanation may come from studies on pesticide use among smallholders in China (Gong, Baylis, Kozak, & Bull, 2016; Liu & Huang, 2013). These studies found that pesticide use is positively correlated with risk aversion. Risk aversion is also a likely explanation in our case for the continued use of chemical inputs. Qualitative interviews with training participants provide support for this hypothesis as several farmers reported they were experimenting with organic farming on only a small piece of their land while continuing to use chemical fertiliser on the remaining land.

## 3.6 Conclusion

In Indonesia, the adoption of organic farming practices remains very low despite efforts of the government and NGOs to promote it nationwide. Information provision in the form

of training or agricultural extension is one potential policy instrument to further increase the adoption of organic farming. We used a randomised controlled trial to investigate the impact of a three-day-training on organic farming in two regions on Java.

While previous studies have shown that information provision and extension services can increase adoption of agricultural practices (e.g Hörner et al., 2019; Kondylis et al., 2017), few studies have examined whether this also applies to organic farming practices, and fewer still by means of a randomised trial. To our knowledge, this is one of the first experimental studies to evaluate the adoption of organic farming technologies. Overall, our findings suggest that intensive training is a promising policy tool to increase the adoption of organic farming. Training led to increased adoption of organic farming practices, improved farmers' knowledge about organic farming, and positively affected their perceptions of organic farming. However, this did not lead farmers to convert completely to organic farming. The most plausible interpretation of our finding is that the training sparked interest and motivated experimentation among training attendees but, unsurprisingly given the short observation window of just one year, had not yet led to a full substitution of organic for chemical inputs by the end of the study. Interestingly, we find that farmers were motivated not only by the price premium that is associated with organic products but also by the prospect of improved soil quality that is associated with organic farming practices.

One noteworthy caveat of our study is the reliance on self-reported organic input use and the lack of information about the quality of these inputs. While we cannot rule out the possibility of a desirability bias affecting our results, this bias is most likely to be small, given the number of follow-up questions we asked farmers who reported using organic fertiliser or pesticide (e.g. on time of adoption, self-production, source of information and motivation for use). We believe that it would be difficult for farmers to answer these follow-up questions convincingly if they were not actually using the organic input. We gain additional confidence from the similarly positive training effects on knowledge levels and the absence of a statistically significant effect on reported chemical fertiliser use. However, while the study identifies a positive short-term effect of training on the use of organic farming practices, further studies are required to evaluate the effects of training on their long-term adoption. Studying long-term adoption will also shed light on the socioeconomic impacts of organic farming adoption, including on-farm profits and farmers' well-being.

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## Appendix

**Table A.3.1:** Differences among info-session non-attendees by treatment group

	Control mean	Treatment mean	p-value
Tasikmalaya	0.56	0.58	-0.02
Male	0.82	0.85	-0.03
Age (yrs.)	55.47	53.19	2.29
Schooling (yrs.)	7.77	7.54	0.22
Asset index	1.64	1.50	0.14
Farming main activity	0.79	0.86	-0.07
Present bias	0.79	0.64	0.15*
Farmers' decisions matter (perc.)	0.54	0.63	-0.08
Agr. env. pollution problem- atic (perc.)	0.33	0.49	-0.16*
Cultivated land	0.29	0.46	-0.17**
Land ownership share	445.01	492.59	-47.58
N	129	112	241

**Table A.3.2:** Testing for systematic attrition (OLS regression)

	(1) Attrition (=1)	(2) Attrition (=1)
Treatment	0.005 (0.013)	0.000 (0.013)
Tasikmalaya	0.058*** (0.018)	0.064*** (0.023)
Male		0.004 (0.019)
Age (yrs.)		0.001 (0.001)
Schooling (yrs.)		0.001 (0.003)
Asset index		0.004 (0.009)
Farming main activity		-0.026* (0.013)
Present bias		0.011 (0.009)
Farmers' decisions matter (perc.)		0.008 (0.016)
Agr. env. pollution problematic (perc.)		-0.013 (0.013)
Cultivated land		0.045 (0.028)
Land ownership share		-0.002 (0.017)
Constant		-0.026 (0.043)
Strata	Yes	Yes
Observations	1,201	1,201
R-squared	0.023	0.038

*Note:* Robust standard errors clustered at village level in parentheses.  
 \*\*\* $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table A.3.3: Outcome variables at baseline and follow-up

	Baseline		C-T	Follow up		C-T
	Control	Treatment		Control	Treatment	
<i>Application</i>						
Organic fertilizer	0.29	0.37	-0.08**	0.27	0.45	-0.18***
Organic pesticide	0.10	0.07	0.04*	0.07	0.14	-0.07***
Processed manure	0.40	0.37	0.02	0.33	0.40	-0.07**
<i>Knowledge</i>						
Labels	0.24	0.21	0.03	0.24	0.46	-0.22***
No land burning	0.67	0.68	-0.02	0.74	0.89	-0.14***
Manure processing	0.67	0.65	0.02	0.77	0.84	-0.07***
Conversion period				0.48	0.66	-0.18***
Buffer zone				0.49	0.71	-0.22***
<i>Perception</i>						
Modern	0.41	0.39	0.02	0.37	0.46	-0.09***
Demand increased	0.17	0.21	-0.04	0.37	0.53	-0.16***
Chemicals neg. env. effect				0.52	0.64	0.12***
Chemicals neg. health effect				0.71	0.78	-0.07***

### 3 ORGANIC FARMING TRAINING

**Table A.3.4:** ITT effects on input application (OLS estimation for treatment arms)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Organic fertilizer	Organic fertilizer <i>produced</i>	Organic fertilizer <i>purchased</i>	Organic pesticide	Organic pesticide <i>produced</i>	Organic pesticide <i>purchased</i>	Processed manure	No chemical fertilizer	No chemical pesticide
Training	0.108*** (0.006)	0.128** (0.014)	0.047 (0.337)	0.051 (0.206)	0.037 (0.303)	0.011 (0.480)	0.046 (0.357)	-0.011 (0.514)	0.016 (0.794)
Training*Video (T*V)	0.046 (0.258)	0.031 (0.640)	0.035 (0.531)	0.026 (0.560)	0.012 (0.746)	0.002 (0.946)	0.040 (0.491)	0.007 (0.761)	0.100 (0.186)
Training*Role-play (T*R)	0.006 (0.861)	0.002 (0.969)	-0.025 (0.627)	0.095 (0.173)	0.063 (0.382)	0.045 (0.153)	-0.004 (0.950)	0.031 (0.237)	0.129* (0.088)
Wald test (p-value) T*V = T*R	0.521	0.587	0.212	0.205	0.451	0.204	0.636	0.377	0.902
Strata	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Outcome	Yes	No	No	Yes	No	No	Yes	Yes	Yes
N	1,146	1,107	1,107	1,146	1,145	1,145	1,146	1,146	1,146

*Note:* \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses.



**Table A.3.5:** ITT effects on knowledge (OLS estimation for treatment arms)

	(1) Labels	(2) No land burning	(3) Manure processing	(4) Conversion period	(5) Buffer zone
Training	0.175*** (0.005)	0.120** (0.015)	0.017 (0.743)	0.138*** (0.007)	0.185*** (0.000)
Training*Video (T*V)	0.012 (0.858)	-0.001 (0.976)	0.025 (0.656)	0.042 (0.442)	0.029 (0.422)
Training*Role-play (T*R)	0.063 (0.373)	0.055 (0.259)	0.127** (0.031)	0.025 (0.706)	0.020 (0.615)
Wald test (p-value) T*V = T*R	0.409	0.159	0.0109	0.788	0.827
Strata	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Lagged Outcome	Yes	Yes	Yes	No	No
N	1,150	1,149	1,150	1,150	1,150

*Note:* \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses.

**Table A.3.6:** ITT effects on perceptions (OLS estimation for treatment arms)

	(1) Modern	(2) Demand increased	(3) More profitable	(4) Chemicals: neg. for env.	(5) Chemicals: neg. for health
Training	0.095** (0.044)	0.100* (0.050)	0.107** (0.032)	0.021 (0.675)	0.033 (0.295)
Training*Video (T*V)	0.015 (0.753)	0.115 (0.105)	-0.025 (0.654)	0.098* (0.072)	0.066* (0.077)
Training*Role-play (T*R)	-0.054 (0.376)	0.012 (0.862)	0.052 (0.326)	0.031 (0.529)	0.037 (0.307)
Wald test (p-value) T*V = T*R	0.233	0.150	0.0997	0.114	0.464
Strata	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Lagged Outcome	Yes	Yes	No	No	No
N	1,150	1,150	1,150	1,150	1,150

*Note:* \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses.

**Table A.3.7:** ITT effects on input application (OLS estimation for heterogeneity)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Organic fertilizer	Organic fertilizer <i>produced</i>	Organic fertilizer <i>purchased</i>	Organic pesticide	Organic pesticide <i>produced</i>	Organic pesticide <i>purchased</i>	Processed manure	No chemical fertilizer	No chemical pesticide
Training	0.175 (0.169)	0.143 (0.246)	0.071 (0.482)	0.211 (0.118)	0.277** (0.040)	-0.025 (0.612)	0.004 (0.978)	0.097 (0.170)	0.277* (0.085)
Training*Age	-0.001 (0.689)	-0.000 (0.973)	-0.000 (0.840)	-0.002 (0.279)	-0.004** (0.048)	0.001 (0.281)	0.001 (0.701)	-0.002 (0.136)	-0.003 (0.198)
Training	0.180** (0.013)	0.183*** (0.009)	0.042 (0.443)	0.081 (0.126)	0.066 (0.252)	0.011 (0.720)	0.050 (0.579)	0.009 (0.799)	0.248*** (0.006)
Training*Years of schooling	-0.007 (0.422)	-0.005 (0.503)	0.001 (0.872)	0.001 (0.789)	-0.001 (0.910)	0.002 (0.593)	0.001 (0.919)	-0.001 (0.818)	-0.019** (0.043)
Training	0.157*** (0.000)	0.152*** (0.000)	0.060* (0.090)	0.090** (0.049)	0.070 (0.121)	0.010 (0.521)	0.096** (0.021)	0.012 (0.544)	0.106* (0.056)
Training*Agr. pollution perceived as problem	-0.068 (0.165)	-0.028 (0.473)	-0.020 (0.674)	0.004 (0.934)	-0.018 (0.642)	0.037** (0.048)	-0.084 (0.120)	-0.024 (0.434)	-0.030 (0.663)
Training	0.149*** (0.000)	0.131*** (0.002)	0.056 (0.174)	0.087** (0.030)	0.060 (0.111)	0.028 (0.197)	0.058 (0.210)	0.027 (0.228)	0.091* (0.094)
Training*Cultivated land size	-0.071 (0.303)	0.024 (0.719)	-0.013 (0.858)	0.013 (0.815)	0.005 (0.912)	-0.005 (0.859)	-0.000 (0.999)	-0.078 (0.220)	0.006 (0.940)
Training	0.081* (0.059)	0.128*** (0.002)	0.038 (0.492)	0.063* (0.070)	0.021 (0.141)	0.045* (0.088)	0.052 (0.302)	-0.024** (0.044)	0.008 (0.910)
Training*Tasikmalaya	0.096* (0.064)	0.024 (0.694)	0.027 (0.644)	0.061 (0.371)	0.087 (0.172)	-0.038 (0.180)	0.014 (0.838)	0.054* (0.068)	0.181* (0.051)
Training	0.124*** (0.000)	0.141*** (0.000)	0.051 (0.158)	0.094*** (0.008)	0.058* (0.067)	0.026 (0.117)	0.062* (0.100)	-0.003 (0.798)	0.084* (0.099)
Training*Self-class. early adopter	0.012 (0.881)	-0.017 (0.835)	-0.003 (0.973)	-0.028 (0.623)	0.023 (0.603)	0.001 (0.985)	-0.032 (0.713)	0.038 (0.394)	0.073 (0.321)
Training	0.130*** (0.000)	0.134*** (0.000)	0.049 (0.137)	0.093** (0.011)	0.060* (0.075)	0.019 (0.219)	0.056 (0.123)	-0.003 (0.835)	0.090* (0.072)
Training*Self-class. high adoption willingness	-0.057 (0.482)	0.073 (0.439)	0.018 (0.864)	-0.042 (0.590)	0.020 (0.752)	0.105** (0.030)	0.035 (0.747)	0.060 (0.231)	0.042 (0.705)
Training	0.176** (0.015)	0.106 (0.192)	0.077 (0.317)	0.044 (0.451)	0.016 (0.735)	0.040 (0.354)	0.131 (0.167)	0.007 (0.170)	0.305*** (0.002)
Training*Present biased	-0.037 (0.525)	0.025 (0.676)	-0.019 (0.755)	0.035 (0.426)	0.034 (0.382)	-0.010 (0.718)	-0.054 (0.399)	-0.004 (0.888)	-0.158** (0.026)
Strata	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Outcome	Yes	No	No	Yes	No	No	Yes	Yes	Yes
N	1,146	1,107	1,107	1,142	1,145	1,145	1,146	1,146	1,146

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses.

**Table A.3.8:** ITT effects on knowledge (OLS estimation for heterogeneity)

	(1) Labels	(2) No land burning	(3) Manure processing	(4) Conversion period	(5) Buffer zone
Training	0.387** (0.013)	0.039 (0.763)	-0.172 (0.203)	0.261* (0.096)	0.298** (0.040)
Training*Age	-0.003 (0.195)	0.002 (0.449)	0.004* (0.090)	-0.002 (0.521)	-0.002 (0.508)
Training	0.090 (0.208)	0.211*** (0.003)	0.083 (0.265)	0.094 (0.304)	0.186** (0.020)
Training*Years of schooling	0.013* (0.084)	-0.009 (0.203)	-0.002 (0.784)	0.008 (0.428)	0.002 (0.830)
Training	0.194*** (0.000)	0.206*** (0.000)	0.083** (0.044)	0.195*** (0.000)	0.203*** (0.000)
Training*Agr. pollution perceived as problem	0.012 (0.821)	-0.149*** (0.002)	-0.035 (0.455)	-0.074 (0.185)	-0.002 (0.974)
Training	0.205*** (0.000)	0.170*** (0.000)	0.096** (0.018)	0.205*** (0.000)	0.248*** (0.000)
Training*Cultivated land size	-0.015 (0.857)	-0.098* (0.054)	-0.089 (0.234)	-0.134 (0.113)	-0.140 (0.102)
Training	0.206*** (0.000)	0.160*** (0.006)	0.096* (0.068)	0.186*** (0.002)	0.204*** (0.000)
Training*Tasikmalaya	-0.014 (0.851)	-0.046 (0.473)	-0.061 (0.327)	-0.054 (0.457)	-0.005 (0.929)
Strata	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Lagged Outcome	Yes	Yes	No	No	No
N	1,150	1,150	1,150	1,150	1,149

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses.

**Table A.3.9:** ITT effects on perceptions (OLS estimation for heterogeneity)

	(1) Modern	(2) Demand increased	(3) More profitable	(4) Chemicals: neg. for env.	(5) Chemicals: neg. for health
Training	0.228 (0.112)	0.219 (0.123)	0.136 (0.355)	0.304*** (0.010)	0.164 (0.143)
Training*Age	-0.003 (0.259)	-0.001 (0.563)	-0.000 (0.887)	-0.004* (0.057)	-0.002 (0.404)
Training	0.270*** (0.001)	0.240*** (0.002)	0.104 (0.187)	0.210*** (0.002)	0.097 (0.146)
Training*Years of schooling	-0.023** (0.018)	-0.012 (0.166)	0.001 (0.865)	-0.018** (0.010)	-0.004 (0.600)
Training	0.093** (0.039)	0.137*** (0.003)	0.130*** (0.006)	0.069* (0.088)	0.081** (0.015)
Training*Agr. pollution perceived as problem	-0.024 (0.699)	0.014 (0.824)	-0.031 (0.608)	-0.010 (0.868)	-0.029 (0.594)
Training	0.099** (0.028)	0.141*** (0.008)	0.101** (0.032)	0.114*** (0.005)	0.102*** (0.001)
Training*Cultivated land size	-0.050 (0.524)	0.007 (0.930)	0.044 (0.603)	-0.153*** (0.014)	-0.107** (0.017)
Training	0.082* (0.053)	0.099* (0.071)	0.107** (0.020)	0.084 (0.116)	0.066* (0.077)
Training*Tasikmalaya	-0.001 (0.992)	0.093 (0.198)	0.018 (0.796)	-0.042 (0.499)	0.002 (0.960)
Strata	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Lagged Outcome	Yes	Yes	No	No	No
N	1,150	1,150	1,150	1,150	1,150

*Note:* \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses.

**Table A.3.10:** LATE effects on input application (OLS estimation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Organic fertilizer	Organic fertilizer <i>produced</i>	Organic fertilizer <i>purchased</i>	Organic pesticide	Organic pesticide <i>produced</i>	Organic pesticide <i>purchased</i>	Processed manure	No chemical fertilizer	No chemical pesticide
ITT	0.126*** (0.000)	0.139*** (0.000)	0.051 (0.131)	0.091*** (0.010)	0.062* (0.052)	0.027* (0.095)	0.058* (0.094)	0.001 (0.933)	0.093* (0.057)
LATE	0.140*** (0.000)	0.154*** (0.000)	0.057 (0.121)	0.101*** (0.007)	0.068** (0.043)	0.030* (0.087)	0.065* (0.084)	0.001 (0.932)	0.103** (0.047)
Strata	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Outcome	Yes	No	No	Yes	No	No	Yes	Yes	Yes
N	1146	1107	1107	1142	1145	1145	1,146	1,146	1,146

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses.

**Table A.3.11:** LATE effects on knowledge (OLS estimation)

	(1) Labels	(2) No land burning	(3) Manure processing	(4) Conversion period	(5) Buffer zone	(6) Knowledge index
ITT	0.200*** (0.000)	0.138*** (0.000)	0.067** (0.038)	0.161*** (0.000)	0.202*** (0.000)	0.759*** (0.000)
LATE	0.222*** (0.000)	0.153*** (0.000)	0.074** (0.029)	0.179*** (0.000)	0.224*** (0.000)	0.842*** (0.000)
Strata	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Outcome	Yes	Yes	Yes	No	No	
N	1150	1149	1150	1150	1150	1150

*Note:* \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses.

**Table A.3.12:** LATE effects on perceptions (OLS estimation)

	(1) Modern	(2) Demand increased	(3) More profitable	(4) Chemicals: neg. for env.	(5) Chemicals: neg. for health
ITT	0.082** (0.015)	0.143*** (0.000)	0.115*** (0.001)	0.064** (0.046)	0.067*** (0.005)
LATE	0.091** (0.011)	0.159*** (0.000)	0.128*** (0.000)	0.071** (0.038)	0.075*** (0.003)
Strata	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Lagged Outcome	Yes	Yes	No	No	No
N	1150	1150	1150	1150	1150

*Note:* \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses.



**Table A.3.13:** Spillover effects (# treatment villages within 5 km radius) on input application (OLS estimation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Organic fertilizer	Organic fertilizer <i>produced</i>	Organic fertilizer <i>purchased</i>	Organic pesticide	Organic pesticide <i>produced</i>	Organic pesticide <i>purchased</i>	Processed manure	No chemical fertilizer	No chemical pesticide
Treatment	0.215*** (0.001)	0.151*** (0.005)	0.077 (0.120)	0.118* (0.053)	0.128** (0.034)	0.013 (0.610)	-0.070 (0.243)	0.012 (0.625)	0.069 (0.435)
Spillover (5km)	0.012 (0.580)	0.009 (0.593)	-0.002 (0.907)	-0.013 (0.455)	0.000 (0.998)	-0.012 (0.241)	-0.078*** (0.001)	0.006 (0.439)	-0.078** (0.021)
Treatment*Spillover	-0.028 (0.396)	-0.009 (0.761)	-0.013 (0.665)	-0.020 (0.352)	-0.035* (0.089)	0.010 (0.425)	0.082*** (0.002)	-0.005 (0.587)	0.035 (0.418)
Strata	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N (POST)	1,149	1,107	1,107	1,149	1,145	1,145	1,149	1,150	1,150
R-squared (POST)	0.080	0.061	0.070	0.064	0.094	0.024	0.060	0.035	0.072

*Note:* \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses. Exposure to treatment villages is measured by the number of treatment villages in a radius of 5km around the villages

**Table A.3.14:** Spillover effects (# treatment villages within 5 km radius) on knowledge (OLS estimation)

	(1) Labels	(2) No land burning	(3) Manure processing	(4) Conversion period	(5) Buffer zone	(6) Knowledge index
Treatment	0.143** (0.014)	0.190*** (0.000)	-0.016 (0.721)	0.070 (0.203)	0.199*** (0.000)	0.585*** (0.000)
Spillover(5km)	-0.071*** (0.000)	0.020 (0.371)	-0.027 (0.291)	-0.059** (0.023)	-0.018 (0.451)	-0.155* (0.074)
Treatment*Spillover	0.043 (0.110)	-0.033 (0.204)	0.050 (0.104)	0.062** (0.040)	0.006 (0.833)	0.127 (0.246)
Strata	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N (POST)	1,150	1,150	1,150	1,150	1,150	1,150
R-squared (POST)	0.184	0.065	0.050	0.131	0.106	0.218

*Note:* \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses. Exposure to treatment villages is measured by the number of treatment villages in a radius of 5km around the villages

**Table A.3.15:** Spillover effects (# treatment villages within 5 km radius) on perception (OLS estimation)

	(1) Modern	(2) Demand increased	(3) More profitable	(4) Chemicals: neg. for env.	(5) Chemicals: neg. for health
Treatment	0.124** (0.021)	0.225*** (0.001)	0.128** (0.013)	0.098* (0.058)	0.066* (0.058)
Spillover (5km)	0.005 (0.812)	0.001 (0.968)	0.003 (0.883)	-0.005 (0.834)	0.001 (0.929)
Treatment*Spillover	-0.025 (0.328)	-0.044 (0.141)	-0.007 (0.709)	-0.017 (0.550)	0.000 (0.983)
Strata	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N (POST)	1,150	1,150	1,150	1,150	1,150
R-squared (POST)	0.113	0.119	0.095	0.107	0.087

*Note:* \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Naive p-values from the Huber-White robust standard errors, clustered at the village level in parentheses. Exposure to treatment villages is measured by the number of treatment villages in a radius of 5km around the villages



# 4 Consumers' Willingness to Pay for organic rice. Insights from a non-hypothetical experiment in Indonesia

*With Michael Grimm and Franziska Steinhübel*

## 4.1 Introduction

Despite efforts to promote organic farming in parts of South and Southeast Asia, it remains a marginal activity in these regions, as it does all over the world. Large-scale adoption of organic farming requires that consumer prices for organic products exceed production costs. Organic farming is usually associated with higher costs due to higher labour intensity and lower yields, although the latter is disputed and seems to depend on local conditions and the crop type under study (Froehlich, Melo, & Sampaio, 2018; Jouzi et al., 2017). Since many smallholders have no access to export markets, sufficient local demand is important to raise adoption rates of organic farming in low- and middle-income countries (Jouzi et al., 2017). Learning about local consumers' Willingness to Pay (WTP) and how it can be enhanced is therefore of interest for policy makers, environmentalists, farmers and other stakeholders promoting organic consumption in this context.

This paper examines consumers' WTP for organic rice in Indonesia. Previous studies have consistently shown that many consumers are indeed willing to pay a price premium for organic products (for reviews see Hamm & Rödiger, 2015; Katt & Meixner, 2020), however, only a few studies have explored this issue in low- and middle-income countries. Existing studies indicate that results are not easily transferable to other country-contexts and products. Probst, Houedjofonon, Ayerakwa, and Haas (2012), for example, found an average price premium of 19% for meals that contain only certified organic vegetables in West-Africa (Benin, Burkina Faso and Ghana). Ha, Shakur, and Pham Do (2019), by

contrast, found evidence for a much higher price premium of 100% for organic choy sum on markets in rural Vietnam and even 200% in urban Vietnam. Further, for certified sustainably-produced rice there is evidence from South Vietnam suggesting a price premium of 9% and up to 33% if additional information on certification and traceability is provided (My et al., 2018).

Generally, in resource-poor settings where households spend an important part of their income on food, one might expect that consumers show a comparably high price sensitivity. However, this should decrease in absolute terms as income increases, i.e. one would expect a positive relationship between income and WTP. Yet the empirical evidence is mixed, it has not been uniformly confirmed in the literature. Some studies found that both household income and consumer prices play an important role in determining the uptake of organic food (Katt & Meixner, 2020; My et al., 2018; Nandi, Bokelmann, Gowdru, & Dias, 2016). Probst et al. (2012), by contrast, found no significant relationship between income and WTP in their sample of West African countries and Wahida, Toiba, Umberger, and Minot (2013) even found a negative relationship in Indonesia.

In this paper, we elicit consumers' WTP for certified organic rice through an incentive-compatible auction mechanism based on the Becker-DeGroot-Marschak (BDM) approach. Our contribution to the literature is twofold. First, it is one of the few studies on WTP for organic products in a lower-middle-income country. Indonesia constitutes a particularly interesting case because the government and various NGOs actively promote organic farming while at the same time consumers' awareness about organic food is still relatively low (David & Ardiansyah, 2017). In contrast to a previous study conducted in Indonesia which relied on stated WTP (Wahida et al., 2013), we use an incentive compatible elicitation approach, which is less prone to a potential 'hypothetical bias' (List & Gallet, 2001). We explore the role of household income and discuss the magnitude of the estimated WTP with respect to the potential of local demand. Second, this article uses randomised low-cost health and environmental information interventions to explore whether these can effectively increase consumers' WTP for organic food. The literature suggests that health and environmental food attributes motivate the purchase of organic food (for a review see Hughner, McDonagh, Prothero, Shultz, & Stanton, 2007). Yet, only a few empirical studies investigated the role of these food attributes in determining consumers' willingness to pay, with rather mixed results (Batte, Hooker, Haab, & Beaverson, 2007; My et al., 2018; Rousseau & Vranken, 2013; Wier, Doherty, Laura, & Millock, 2008). In particular, this is one of the first studies to causally assess the effect of additional information (rather than pre-existing health or environmental concerns) on consumers' WTP for organic food. Aoki, Akai, Ujiie, Shimmura, and Nishino (2019) emphasise the importance of

a non-hypothetical set-up for the practical validity of WTP estimates. This is particularly relevant when exploring the potential of an information treatment. Otherwise, any observed effect might measure social desirability bias rather than a potential change in actual WTP. We further expand the discussion on the role of these food attributes by comparing the effect of information on revealed WTP and stated consumption intention. Related studies found that additional information on animal welfare or certification increased respondents' WTP for organic bacon in the UK (Akaichi, Glenk, & Revoredo-Giha, 2019) and sustainable rice in Vietnam (My et al., 2018), respectively. However, given the different country context and food attributes under consideration in this study, it remains unclear whether additional information on health and environmental friendliness will also raise WTP for organic rice in Indonesia.

The remainder of this paper is organized as follows: Section 4.2 describes the country context. Section 4.3 outlines the conceptual framework. Section 4.4 describes the experimental set-up, sample characteristics, and statistical analysis. Section 4.5 presents the results. Section 4.6 discusses the results and section 4.7 concludes.

## 4.2 Context

This study is set in the Special Region of Yogyakarta (hereafter Yogyakarta), Java. As in many other regions in Indonesia, agriculture in Yogyakarta is associated with poverty. This makes it even more important that any proposed alternative to the currently practised agricultural methods is economically viable for farmers. Hence, price premiums are important to increase the attractiveness of organic farming among farmers.

Currently, the Indonesian agricultural sector is characterised by high levels of chemical inputs. The over-application of chemical inputs has long been associated with land degradation in Indonesia (Simatupang & Timmer, 2008). Next to land degradation, biodiversity loss and water pollution are further important concerns, which are associated with chemical-intensive conventional farming. Concerns about the adverse environmental impacts of chemical intensive conventional farming have prompted various initiatives that promote organic farming (David & Ardiansyah, 2017). Introduced by local non-governmental organisations in the 1980s, organic farming started to attract policy makers' interest in the early 2000s. In 2001, the Ministry of Agriculture launched the 'Go Organic 2010' campaign, which envisioned Indonesia to become one of the World's main producers of organic food by 2010. Although it did not achieve this goal, this initiative still provides the impetus for moves towards the institutionalization of Indonesia's organic farming sector (Jahroh, 2010). While a small domestic market exists, the current national

policy focus is on promoting organic products as a profitable export commodity.

Organic rice is currently the most important organic product in terms of export volume and domestic consumption (David & Ardiansyah, 2017). At the time of our study (2018), organic rice prices differed greatly across points of sale in Yogyakarta. Local farmers, for example, asked prices as low as IDR 13,000 (US\$ 0.96) per kilo for uncertified organic white rice <sup>1</sup> and IDR 15,000 (US\$ 1.10) per kilo for certified organic rice (however, it should be noted that these farmers received financial support for the certification). In contrast, supermarkets sold organic certified rice for around IDR 20,000 (US\$ 1.47) per kilo, and sometimes for even higher prices. Despite an increasing number of supermarkets in Indonesia, most urban consumers continue to buy rice and other food products at traditional markets, small local food shops or directly from the farmer. In 2018, prices for conventionally grown rice ranged between IDR 9,500 (US\$ 0.70) and IDR 13,500 (US\$ 0.99) at traditional markets in Yogyakarta. Quality determinants explain most of this price range (e.g. rice variety or freshness).

### 4.3 Conceptual Framework and Hypotheses

Following Lancaster (1966), we assume that consumers derive utility from a bundle of different attributes rather than from the product itself. Consumers' motivation to pay a price premium for organic food thus depends on food attributes that differentiate it from conventionally produced food. We suggest that there are at least three food attributes which may motivate consumers to pay a price premium for organic food: health benefits, environmental benefits and higher quality (see Figure 4.1).

The perceived *health benefits* of organic food over conventional food include the absence of chemical residues and higher nutritional quality. *Environmental benefits* derive from the different ways that organic farming is more 'environmentally friendly' than conventional farming. *Higher quality* refers to aspects such as taste and freshness. However, as Custodio et al. (2019) showed, quality perception often differs among consumers, contexts and geographic areas.

We further suggest that consumers' trust in the product affects their willingness to pay a price premium for organic food. Trust derives from consumers' belief that the product in question was indeed produced according to organic principles. Labels can increase consumers' trust and hence their WTP because they reduce information asymmetries between consumers and producers (Rousseau & Vranken, 2013). Assuming that consumers value the described food attributes and trust that the product is produced according to

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<sup>1</sup>In this paper, we only refer to white rice and not to other rice types such as brown or red rice.



organic principles, we derive our first hypothesis:

*Hypothesis 1: Consumers are willing to pay a price premium for organic food.*

In a context in which many consumers face financial constraints, the WTP is expected to be determined not just by the consumer's taste but also by the consumer's income, i.e. the budget consumers have at their disposal to purchase food. Consumers with low income may need to focus on food quantity rather than food quality. Some consumers may therefore be unable to afford organic food, irrespective of their valuation of organic food attributes. This leads us to our second hypothesis:

*Hypothesis 2: A consumer's WTP for organic food increases with income.*

Lastly, consumers differ in terms of their exposure to information about organic food and their valuation of organic food attributes, which in turn implies differences in their WTP. We expect that informing consumers about a beneficial organic food attribute increases their WTP. Our third hypothesis is thus:

*Hypothesis 3: Information on health and environmental benefits increases a consumer's WTP for organic food.*

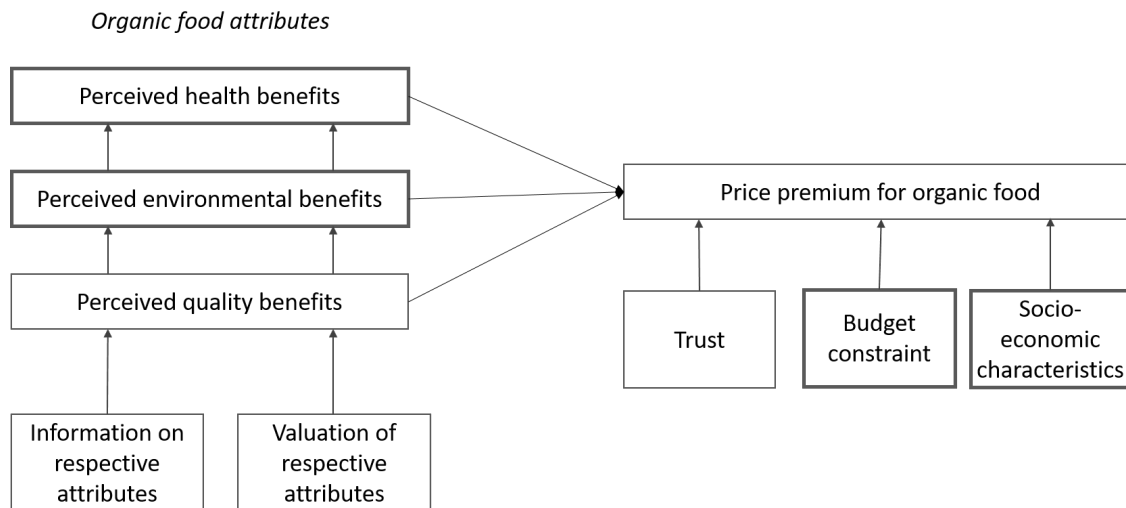
Socio-economic characteristics such as age, education, gender and household size might also be correlated with the willingness to pay a price premium for organic food. This framework, shown in Figure 4.1, assumes that socio-economic characteristics only have a direct influence on the WTP. In reality, they will of course also determine income and affect exposure to information and how this information is processed. Yet given our sample size of less than 300 respondents and hence limited power, an empirical analysis of such interactions is beyond the scope of this paper.

## 4.4 Experimental set-up

### 4.4.1 Design and Implementation

We chose rice for our experiment, as it is frequently purchased by almost all consumers in Indonesia (Reardon et al., 2014). We used certified rice to increase people's trust in the organic quality of the rice. Indonesian consumers are generally familiar with the concept of certification as other certificates like 'halal' are common. The rice for the experiment was purchased from a local organic farmer in Yogyakarta.

We used a BDM approach to elicit respondents' WTP for organic rice (Becker, Degroot, & Marschak, 1964). Using the BDM method, respondents make a price bid to purchase the product. This bid is subsequently compared to a randomly drawn price. Respondents



**Figure 4.1:** Conceptual framework for determinants of WTP premium for organic food

*Source:* Own representation

can only purchase the product if their bid is at or above the randomly drawn price. In this case, they pay the randomly drawn price and receive the product. We opted for the BDM approach because, unlike other approaches, it provides an incentivized measure to reveal consumer preferences. If respondents overstate their real reservation price, they might (depending on the drawn price) have to buy the product at a price higher than their actual valuation. In contrast, by understating the real reservation price, respondents might miss a purchase opportunity at a price that was less than or equal to their valuation. Another useful feature of the BDM approach is that it allows observation of exact point-of-purchase prices, i.e. it allows to draw a detailed demand curve (Cole, Fernando, Stein, & Tobacman, 2020). Thereby it provides more precise information on the respondents' WTP than a take it or leave it approach, which provides only upper and lower WTP bounds. Furthermore, a growing number of empirical studies have used the BDM approach in low- and middle-income countries and there is evidence that WTP estimates align well with actual market outcomes in these contexts (Mastenbroek, Sirutyte, & Sparrow, 2021). While the BDM approach was deemed most suitable in the context of this study, there are also debates whether it is truly incentive compatible, especially if respondents are not maximizing their expected utility (Horowitz, 2006). Furthermore, there are concerns that the BDM approach is complex and difficult to understand (Alphonse & Alfnes, 2017; Grimm, Peters, Lenz, & Sievert, 2020). To address this concern, enumerators demonstrated the bidding process in detail using a graphical illustration with a different product.

We combined the BDM approach with two information treatments to investigate whether information on health or environmental benefits can effectively increase consumers' WTP

for organic food. Respondents were randomly assigned to either one of the two treatment groups or to the control group by assigning households to treatments in the order they were interviewed. Each information treatment consisted of a short video, providing information about either the health benefits of organic food or the environmental benefits of organic farming. In both videos, a local farmer shares his personal experience. We chose to present the information as a mixture of audio comments and pictures, with very little printed text, to make the videos easy to understand and to be inclusive of illiterate respondents. The control group was not shown a video but only briefly verbally introduced to the basic principles of organic farming.

**Table 4.1:** Sample composition

Group 1	Group 2	Group 3
Video on health benefits	Video on environmental benefits	No video treatment

The experiment was conducted only in urban and sub-urban areas of Yogyakarta because we expected a relatively low market potential in rural areas: firstly, rural households are more likely to be rice producers themselves or purchase rice directly from farmers in their village; secondly, the purchasing power in rural areas is, on average, lower. We used a two-stage random sampling procedure on the community and household level to select the respondents for this study. In the first stage, we sampled 19 areas in Yogyakarta. In the second stage, households were randomly selected by enumerators, who set out from a mosque in a randomly assigned direction (for more details on the sampling procedure see Appendix B).

The overall procedure of the experiment was as follows: first, the enumerator introduced the study to the members of the household and informed them about the opportunity to purchase one kg of certified organic rice. The enumerator then invited the household member who is usually responsible for food shopping to take part in an interview. In most cases, this resulted in an interview with a female household member. Having obtained the respondent's consent to participate in the study, the enumerator explained the experiment in detail using a graphical illustration. The enumerator emphasized that the experiment included an actual transaction and that the respondent would have to purchase the rice if she or he won the bidding game. Following the explanation and time to inspect the rice, respondents in the treatment groups were shown the respective information video, while respondents in the control group were given only short verbal information. Then all respondents were asked to submit a price bid for one kg of certified organic rice. The price distribution was not announced to avoid any anchoring effects or strategic bidding.

After submitting their bid, respondents drew a price out of the price pool. Respondents who submitted a bid higher or equal to the drawn price purchased the rice for the drawn price.

After the WTP experiment, the respondents were interviewed using a structured survey questionnaire. Respondents received no financial incentive for their participation. The experiment was carried out in April 2018 and conducted in Indonesian (Bahasa Indonesia).

#### 4.4.2 Sample Characteristics

Table 4.2 summarizes the results of the survey. The majority of the respondents were female (71%), married (92%) and Muslim (86%). The second most common religion in our sample was Christianity. Respondents were on average 45.5 years old, with age ranging from 19 years to 82 years. Educational attainment was high with on average 12.8 years of schooling. This is slightly higher than average years of schooling in Yogyakarta city (11.4 years) and might be due to the focus on (sub-)urban areas (Bappeda Jogja, 2020). Around 36% of the respondents were not engaged in an economic activity at the time of the study but classified themselves as homemaker (24%), pensioner (8%), student (3%) or simply not engaged in any economic activity (2%). Since respondents were reluctant to answer direct questions about income, we asked respondents which of the following three income groups their household belonged to: a monthly household income (1) below IDR two million (US\$ 147.06), (2) between IDR two million and IDR five million (US\$ 367.65) and (3) above IDR five million. IDR two million correspond to the minimum wage in Yogyakarta and thus households that fall in the first category might be classified as relatively poor. In our sample, around 26% of the respondents reported that their household was in the lowest income group 1. Slightly more than half of the respondents (53%) reported that their household was in income group 2 while 21% of the respondents reported that their household was in income group 3, the highest income group. Average household size was 4.3 persons. When asked about their exposure to environmental pollution, 19% of respondents reported that their perceived level of exposure is high or very high. We further asked respondents which characteristics they attribute to organic food. Almost 80% of the respondents stated that they perceived organic food to be healthier than conventionally produced food.

Balance tests for randomised information treatment indicate no systematic difference between the treatment groups and the control group (for details see Appendix Table A.4.1). In the majority of cases, pairwise differences between characteristics of respondents in different groups are not statistically significant. While there are statistically significant differences for some variables, in most cases the significance levels are low. In our analysis,

we address this potential source of bias by introducing these variables as controls.

**Table 4.2:** Variables description and sample characteristics (N=293)

Variable	Description	Mean (Std. dev.)
<i>Socioeconomic characteristics</i>		
Female	1 = female; 0 otherwise	0.71
Age	Age of the respondent in years	45.51 (12.83)
Married	1 = married; 0 otherwise	0.92
Religion		
Muslim	1 = Muslim; 0 otherwise	0.86
Christian	1 = Christian; 0 otherwise	0.12
Other religion	1 = neither Muslim nor Christian; 0 otherwise	0.02
Years of schooling	Completed years of schooling in years	12.80 (3.79)
Household size	Household size (number of people living under the same roof)	4.32 (1.50)
Income		
Income group 1	1 = household income is below IDR 2 million; 0 otherwise	0.25
Income group 2	1 = household income is between IDR 2 - 5 million; 0 otherwise	0.55
Income group 3	1 = household income is above IDR 5 million; 0 otherwise	0.20
<i>Perception of environmental pollution and organic consumption</i>		
Perceived env. pollution	1 = respondent perceives exposure to env. pollution as high or very high	0.19
Perceived benefits organic consumption		
Healthier	Respondent perceives organic food to be healthier	0.83
Environmentally friendly	Respondent perceives organic food to be environment friendly	0.05
Quality	Respondent perceives organic food to be of higher quality	0.06
<i>Purchasing behaviour</i>		
Past organic rice purchase	1 = respondent purchased organic rice in the past; 0 otherwise	0.47
Last rice purchase price	Price respondent paid for 1kg of rice in IDR last time respondent bought rice	11,448 (1,605)
Expected organic rice price	Market price respondent expects for 1kg of certified organic rice	15,585 (3,615)

### 4.4.3 Empirical Specification

To test our first hypothesis, we simply compare the revealed WTP for organic rice and the recall price, i.e. the price the respondent reportedly paid during the last (non-organic) rice purchase. Additionally, we use a second benchmark and compare revealed WTP to the common price for high quality conventional rice. This should give us a relatively close estimate for the premium the respondent is willing to pay for the attributes that distinguish organic rice from conventional rice, i.e. health, environmental and quality attributes. Yet, it should be noted that this is only an estimate rather than the exact WTP as part of the offered price might reflect food attributes that are unrelated to organic rice such as the purchasing environment (during an experiment rather than at the farmer/market/supermarket). Indeed, some studies found that the point of purchase (e.g. different store types) influences WTP for organic food (Ellison, Bernard, Paukett, & Toensmeyer, 2016).

In line with our conceptual framework, we then regress respondents' WTP for one

kilogram of organic rice on income group, information treatment, and on additional socio-economic characteristics. Given the absence of zero bids and the continuous character of our dependent variable, a linear regression model of the following form is suitable:

$$WTP_{ij} = \beta_0 + \beta_1 I_{ij} + \beta_2 H_{ij} + \beta_3 E_{ij} + \beta_4 X_{ij} + \varepsilon_{ij} \quad (4.1)$$

where the index  $i$  indicates the respondent and  $j$  the area of residence.

To analyse the relationship between income and respondents' WTP (hypothesis 2) we include the vector  $I_{ij}$  which encompasses two binary variables capturing whether respondents' household income is in the middle-income group or the high-income group respectively. The low-income group serves as the reference category. Two dummy variables,  $H_{ij}$  and  $E_{ij}$ , are included to analyse the role of the health and environment information treatment (hypothesis 3) respectively. These dummies take the value of one if respondent  $i$  in area  $j$  was shown the respective informational video. For respondents in the control group, both dummies take the value zero. Additionally, we include a vector  $X_{ij}$  which controls for respondents' individual and household characteristics, perceptions about benefits of organic food consumption and perceived exposure to environmental pollution as well as purchasing behaviour. Standard errors are clustered at the area level.

We further re-estimate the regression model above but with consumption intention as outcome instead of the revealed willingness-to-pay. During the survey, respondents were asked whether they plan to consume organic products in the future (with the answer options: 'yes', 'maybe', and 'no'). In our main estimation specification, we code both 'yes' and 'maybe' as 'one' and 'no' as 'zero'. However, we also test other coding possibilities and show the results of a probit model for the binary outcome (in the Appendix).

## 4.5 Results

### 4.5.1 Revealed WTP

Table 4.3 shows that respondents were willing to pay an average price of IDR 13,771 (US\$ 1.01) for one kilo of certified organic rice. The price bids ranged from IDR 9,000 (US\$ 0.66) to IDR 25,000 (US\$ 1.84). Comparing the bids for organic rice and the price that participants reportedly paid the last time they bought conventional rice, suggests that participants are on average willing to pay a price premium of 20.1% for organic rice compared to the rice price they commonly pay. High quality rice (at local markets) was priced at around IDR 12,000 (US\$ 0.88) to IDR 13,500 (US\$ 0.99) at the time of the study. The average offered price for organic rice lies slightly above the upper bound for

high quality rice. Overall, this provides support for our first hypothesis and suggests that, on average, consumers value the food attributes that differentiate organic rice from conventional rice. The majority of respondents (74%) offered a higher price, 17% offered the same price and 9% offered a lower price for the organic rice compared to the last price paid for conventional rice. 194 respondents (66%) submitted bids above or equal to the randomly drawn price and hence purchased the organic rice.

**Table 4.3:** Bidding game outcomes (in IDR), full sample and by treatment status

	Full Sample	Health Information Treatment Group	Environment Information Treatment Group	No Video Group
Mean bid amount	13,788 (2,974) N=293	14,037 (3,111) N=108	13,705 (2,991) N=88	13,588 (2,808) N=97
Mean reported price of conventional rice	11,448 (1,605) N = 293	11,613 (1,637) N = 108	11,489 (1,821) N = 88	11,228 (1,326) N = 97
Expected price for organic rice	15,585 (3,615) N=261	15,378 (3,191) N = 94	15,766 (3,668) N = 79	15,645 (4,003) N = 88

*Note:* Standard deviation in parenthesis

Figure 4.2 shows the demand curve.<sup>2</sup> From this curve, one can read the uptake for specific prices.<sup>3</sup> For example, about 44% of the sample would take up organic rice for IDR 15,000 (US\$ 1.10), the price for which we purchased the rice directly from the farmer. To reach at least 80% of the sample the price would need to be at or below IDR 11,000 (US\$ 0.81). Uptake decreases considerably for higher market prices, for example those prevailing in supermarkets. Only 25 respondents offered at least IDR 20,000 (US\$ 1.47), the common lower bound price for a supermarket.

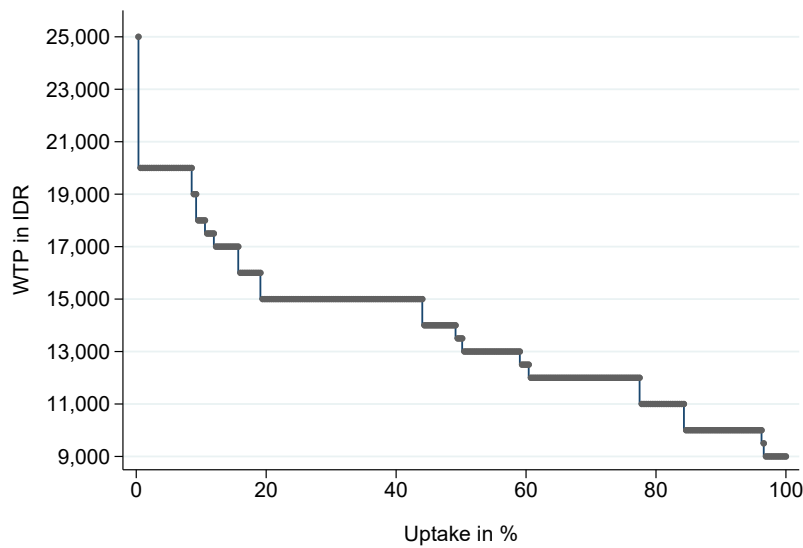
## 4.5.2 The Role of Income

The regression results shown in Table 4.4 allow exploring the correlation between the revealed WTP and income, the information treatments and socio-economic characteristics. In this sub-section, we first focus on the role of income. We also explore the correlation of income and stated consumption intentions (Table 4.5).

Considering the coefficients shown in cols. 5 and 6 of Table 4.4, we find sizeable income effects. This is in line with our second hypothesis. From the low-income group to the

<sup>2</sup>Looking at the distribution of the submitted prices, one can observe a large number of price bids around the interval levels of IDR 1,000 (US\$ 0.07), i.e. bids made in thousands of Rupiahs. This is not surprising as prices are typically given in thousands or five hundreds of Rupiahs on the local market.

<sup>3</sup>However, as noted before (Section 4.4.3), different purchase situations might influence the WTP to some extent.



**Figure 4.2:** Demand curve (full sample)

*Source:* Own representation

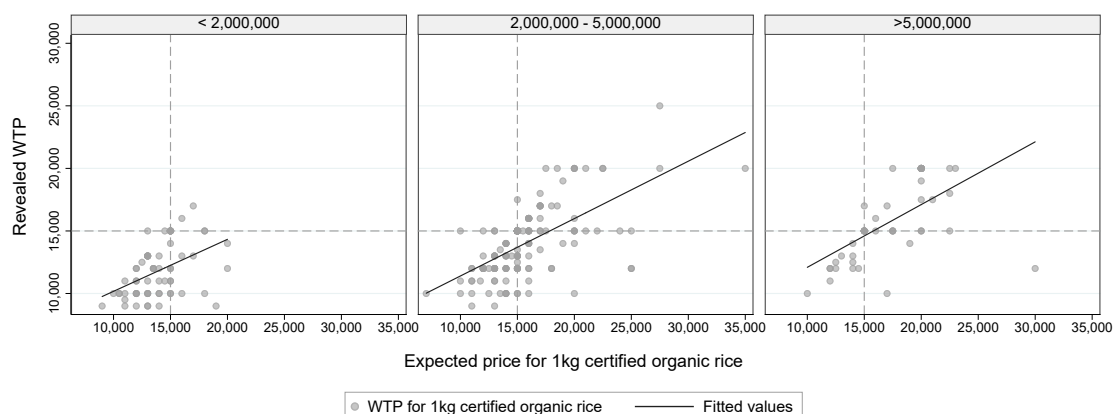
middle-income group the WTP increases by about IDR 1,210 (US\$ 0.09) (9%); from the middle-income group to the high-income group the WTP further increases by around IDR 862 (US\$ 0.06) (6%). Interestingly, income not only determines the WTP but also ‘price expectations’, i.e. the price participants expected to encounter when they buy organic rice at a local retailer (see Figure 4.3). Notably, the relationship between price expectations and WTP is positive in all income groups. This positive relationship is also confirmed if explored in a regression framework (see col. 3 of Table 4.4). However, in the lowest income group the majority of respondents reported price expectations below IDR 15,000 (US\$ 1.10). This clustering is less evident in the other two income groups. Overall, this indicates that income groups differ not only in revealed WTP but also in market perceptions.

In contrast to revealed WTP and price expectations, there are no significant differences between the low and middle-income group with respect to future consumption intentions. However, results reported in col. 3 (Table 4.5) show that respondents in the high-income group are 17% more likely to state that they intend to include organic food in their future diet than respondents in the low-income group.

### 4.5.3 Effects of Information Treatments

Contrary to our third hypothesis, the treatment effects did not significantly influence respondents’ WTP for organic rice. While Table 4.3 shows that the bids made in the two treatment groups were on average slightly higher than in the control group, the treatment





**Figure 4.3:** Relationship between price expectations and WTP by income group

*Source:* Own representation

effects are not statistically significant if they are estimated in a regression framework (Table 4.4). To achieve a statistical power of 80%, with a significance level of 5%, our sample size allows consideration of differences as small as IDR 889 (US\$ 0.07). This implies that we cannot exclude that there are differences in average bids across the control and treatment groups; but if there are differences, they are likely relatively small. Therefore, we conclude that the information treatments were not effective in substantially raising the consumers' WTP.

When asked about the benefits of consuming organic food, almost 83% of respondents referred to health benefits, while only 4% referred to environmental benefits. Surprisingly, given that the questions were asked after respondents in the treatment groups had seen the videos, the reference to either health or environmental benefits was not appreciably higher in the corresponding treatment group (see Table A.4.2 in the Appendix).

Yet, looking at stated consumption intentions (Table 4.5), the results suggest at least some effects, albeit small. Respondents who were exposed to the health video were 10% more likely to state that they plan to include organic food in their diet in the future. Yet, this effect is only significant at the 10% level and is not robust across all specifications (see section 4.5.5). The effect of the environment video is slightly higher at 14% and significant at the 5% level. We can of course not judge whether this is a lasting effect and hence consumers do indeed buy more organic food in the future. Moreover, stated consumption intentions might be affected by 'hypothetical' or 'social desirability' bias.

#### 4.5.4 Socio-economic Characteristics and WTP

This section explores correlations between the revealed WTP and a whole range of other socio-economic characteristics as well as perceived exposure to environmental pollution, past experience with organic rice and the last rice purchase price (Table 4.4, col. 5 & 6). The results suggest that gender or being married has no statistically significant effect on respondents' WTP. Further, we find no significant and consistent relationship between WTP and education or household size. While results indicate statistically significant age effects, they are quite small. Each additional year of age reduces the willingness to pay by about 0.3% or by about IDR 38 (US\$ 0.003). Comparing respondents of Christian religion with respondents of Muslim religion, we find that the WTP of Christians exceeded that of Muslims by 7% or by about IDR 867 (US\$ 0.06). The differences among religious affiliations might be related to specific cultural customs such as haggling. While haggling is in some cultural or religious groups very common, Canavari, Drichoutis, Lusk, and Nayga (2019) stated that it remains unclear how such practices unfold in experimental settings. Future research could further explore whether the effects associated with religion are rooted in differences in how different religions define and interpret the interaction between humans, health and the environment.

The WTP of respondents who perceived their exposure to environmental pollution as high was on average 5% higher than the WTP of those who did not. The coefficient is statistically significant at the 5% level. This suggests that environmental awareness is positively correlated with the WTP for organic rice. Yet, only 4% of the sample said they associated organic food with environmental benefits. Table 4.4 further shows that reference to health has a positive and statistically significant effect on respondents' revealed WTP whereas the reference to quality and environment has no statistically significant effect.

Whether respondents had previously bought organic rice has a moderate effect on their WTP for organic rice; past organic rice purchase increases respondents' WTP by about 4%. Interestingly the most recent purchasing price for conventional rice also has a statistically significant effect on respondents' WTP for organic rice. The elasticity reported in col. (6) implies that a 1% increase in the price paid for conventional rice translates into a 0.58% increase in the bid price for organic rice. Given the usual price intervals of IDR 500 (US\$ 0.04) – IDR 1000 (US\$ 0.07) used in setting prices for conventional rice, this is a sizeable effect.

**Table 4.4:** Correlates of WTP (OLS regressions)

	(1) WTP	(2) WTP	(3) WTP	(4) WTP	(5) WTP	(6) ln WTP
<i>Income (Ref. Income group 1 &lt;IDR 2m)</i>						
Income group 2 (IDR 2m - IDR 5m) (=1)	2,114.22*** (365.99)	1,214.53*** (405.55)	809.32** (349.50)		1,210.42*** (409.18)	0.09*** (0.03)
Income group 3 (>IDR 5m) (=1)	3,859.44*** (421.86)	2,078.58*** (323.43)	1,327.93*** (432.43)		2,072.37*** (316.63)	0.15*** (0.02)
Price expectations (IDR )			0.39*** (0.04)			
<i>Information treatment</i>						
Health information (=1)				428.73 (452.64)	95.95 (335.52)	0.00 (0.02)
Environment information (=1)				98.64 (504.52)	-127.05 (341.22)	-0.01 (0.03)
<i>Socioeconomic characteristics</i>						
Female (=1)		-599.36 (368.86)	-649.96** (262.31)		-619.26 (377.00)	-0.05 (0.03)
Age (in yrs.)		-38.23*** (12.14)	-21.31** (9.07)		-38.22*** (12.12)	-0.00*** (0.00)
Married (=1)		-422.72 (455.01)	-154.19 (403.14)		-405.26 (472.06)	-0.02 (0.04)
Religion (Ref. Muslim)						
Christian (=1)		899.11*** (281.56)	534.48* (273.69)		867.33*** (272.83)	0.07*** (0.02)
Other religion (=1)		-705.97 (714.36)	-223.17 (1,161.33)		-744.27 (709.27)	-0.05 (0.06)
Years of schooling (in yrs.)		-12.44 (43.73)	-2.12 (40.28)		-12.49 (44.50)	-0.00 (0.00)
Household size		-51.71 (136.04)	70.91 (118.66)		-53.20 (133.54)	-0.00 (0.01)
<i>Perception of env. pollution &amp; organic consumption</i>						
Perceived environmental pollution (=1)		715.27** (288.80)	483.35 (355.54)		709.78** (308.75)	0.05** (0.02)
Perceived benefits organic consumption						
Healthier (=1)		677.17* (370.75)	224.66 (245.25)		659.50* (370.03)	0.06** (0.03)
Environmentally friendly (=1)		-119.51 (600.62)	-837.74 (769.21)		-125.36 (591.24)	0.01 (0.04)
Quality (=1)		87.95 (740.51)	-900.44 (601.92)		57.15 (716.37)	0.01 (0.05)
<i>Purchasing behaviour and price expectations</i>						
Past organic rice purchase (=1)		576.81* (294.02)	104.95 (280.99)		608.51** (291.38)	0.04** (0.02)
Last rice purchase price (IDR or log depending on dep. var)		0.71*** (0.09)	0.57*** (0.10)		0.71*** (0.09)	0.58*** (0.08)
Weekend dummy (=1)	yes	yes	yes	yes	yes	yes
Intercept	11,932.90*** (258.16)	6,532.83*** (1,424.18)	1,518.18 (1,243.83)	13,750.69*** (382.04)	6,572.24*** (1,446.53)	4.13*** (0.75)
Observations (N)	293	293	261	293	293	293
Adjusted R-squared	0.19	0.40	0.57	-0.00	0.40	0.41

*Note:* There are less observations for col. 3 as some respondents refused to provide price expectations if they did not know 'organic'. Standard errors are in parenthesis. Standard errors are clustered at the area level. \*\*\*p<0.01, \*\*p<0.05, \*p<0.10

**Table 4.5:** Correlates of Consumption Intentions (OLS regression)

	(1) Consumption Intention	(2) Consumption Intention	(3) Consumption Intention
<i>Income (Ref. Income group 1 &lt;IDR 2m)</i>			
Income group 2 (IDR 2m - IDR 5m) (=1)	0.05 (0.08)		-0.00 (0.08)
Income group 3 (>IDR 5m) (=1)	0.28*** (0.07)		0.17** (0.07)
<i>Information treatment</i>			
Health information (=1)		0.12* (0.07)	0.10* (0.06)
Environment information (=1)		0.19*** (0.06)	0.14** (0.06)
<i>Socioeconomic characteristics</i>			
Female (=1)			-0.11** (0.05)
Age (in yrs.)			-0.01*** (0.00)
Married (=1)			0.20* (0.11)
Religion (Ref. Muslim)			
Christian (=1)			-0.01 (0.08)
Other religion (=1)			0.18 (0.12)
Years of schooling (in yrs.)			-0.01 (0.01)
Household size			0.00 (0.02)
<i>Perception of env. pollution &amp; organic consumption</i>			
Perceived environmental pollution (=1)			0.02 (0.06)
Perceived benefits organic consumption			
Healthier (=1)			0.19** (0.07)
Environmentally friendly (=1)			0.23* (0.13)
Quality (=1)			0.14 (0.09)
<i>Purchasing behaviour and price expectations</i>			
Past organic rice purchase (=1)			0.24*** (0.06)
Weekend dummy (=1)	yes	yes	yes
Intercept	0.59*** (0.07)	0.58*** (0.06)	0.65** (0.28)
Observations (N)	293	293	293
Adjusted R-squared	0.04	0.02	0.15

### 4.5.5 Robustness Analysis

To test the robustness of our findings, we repeated the estimations with the full sample that includes the dropped observations. Table A.4.3 in the Appendix shows that the results are very similar across both samples. Furthermore, we tested whether the WTP results are robust to different model specifications. Firstly, to account for the possibility that respondents might have been influenced by their knowledge of price levels outside the auction, a left-censored Tobit model was estimated where bids are assumed to be censored at the stated average price level of conventional rice as the lower limit (IDR 11,465 (US\$ 0.85)). Secondly, another Tobit model was estimated to account for the possible influence of outlier bids by bottom- and top-coding at 5% and 95% of the distribution of the submitted prices. Thirdly, we estimated an interval-censored regression model as most of the submitted bids were at intervals of IDR 1,000 (US\$ 0.07), which is also how prices are advertised in local markets. However, respondents' true WTP may well lie between those values. In estimating the model, we set the lower and upper bounds as IDR 500 (US\$ 0.04) below and above the submitted bid prices. Table A.4.4 in the Appendix reports the estimates for the OLS regression with the left-censored Tobit regression, the bottom and top-coded Tobit regression and the interval-censored regression. It can be noted that the model specification does not significantly affect the results, i.e. estimates are similar in sign and significance.

We further tested whether the consumption intention results are robust to the exclusion of the 'maybe' answers and the estimation of probit and an ordered probit models. Table A.4.5 in the Appendix reports the results. The positive effect of being in household income group 3 and the effect of the environmental video are robust across all specifications. However, the effect of the health video is not statistically significant if 'maybe' answers are excluded (col. 2). It is also not statistically significant in the ordered probit model specification (col. 5).

## 4.6 Discussion

Consistent with the literature and in line with our first hypothesis, we find that respondents are indeed willing to pay a price premium for organic rice. On average, this price premium amounts to 20.1% more than respondents paid for conventional rice the last time they bought it outside of our experiment. This premium seems in range of organic food premiums identified by previous studies in low- and middle-income countries (e.g. My et al., 2018; Probst et al., 2012). The findings also confirm our second hypothesis that the WTP for organic rice is increasing in income. While this is in line with studies from India

(Nandi et al., 2016) and Vietnam (My et al., 2018), it is in contrast to prior research in Indonesia by Wahida et al. (2013). The latter is particularly surprising as the sample under study is very similar to ours, urban consumers in Java, Indonesia. One potential explanation could be that this study used an incentive compatible elicitation approach while Wahida et al. (2013) investigated stated WTP. Potentially, poorer consumers are more likely to state prices they would like to pay rather than prices they can afford to pay.

This study further examined whether WTP can be raised by providing respondents with information about the health and environmental benefits of organic rice. Maybe not completely unexpected given the light form of the treatments, we found that the information treatments did not significantly increase respondents' WTP. There are several possible explanations for the absence of a treatment effect in our study. First, it is possible that the video on the health benefits of organic rice simply did not provide enough new information. Maybe respondents were already aware of the health benefits of organic food or the information given during the introduction regarding the absence of chemical residues was already interpreted as a health benefit. The additional information content from the video may have then been insufficient to affect respondents' perceptions. This is consistent with the existence of a statistically significant correlation between perceived health benefits and respondents' WTP. It is also in line with the finding that health benefits were the most frequently mentioned positive attribute of organic food among all respondents, irrespective of the treatment group. The results might be interpreted as a signal that health attributes are a relevant factor for consumers' WTP, but that our video was not effective in changing respondents' perceptions of these benefits. Yang, Pebriyani, Ujiie, Wann, and Chen (2021), for example, found that food safety concerns were listed as most important food value among Indonesian participants in an online survey. Second, the generally low level of environmental awareness among respondents might explain why the video on environmental benefits was also ineffective in raising their WTP. A study in China also found that highlighting the environmental benefits of organic food had a positive effect only among respondents who had previously reported strong pro-environmental values (Loebnitz & Aschemann-Witzel, 2016). Third, and related to the previous two explanations, it could be that the effectiveness of information provision was limited by the mode of information delivery. It may well be that increasing consumers' valuation of a benefit requires repeated exposure to information and persuasive arguments and that a onetime exposure is not sufficient. Future research on different communication methods could explore this in more detail.

Interestingly, we find a positive and statistically significant relationship between expo-

sure to the environment video and stated consumption intention. Given the absence of a significant effect on revealed WTP, this could be interpreted as signal for social desirability bias. Potentially, respondents expected that consumption in line with environmental protection is socially desirable (or desired by the research team) but placed too little value on it for themselves to adjust their WTP for organic rice. This interpretation is in line with Wier et al. (2008) who demonstrated that there is a significant discrepancy between stated preferences for public good attributes such as environmental benefits and actual purchase behaviour among Danish survey respondents. The contrasting effect of environmental information on stated consumption intention and revealed WTP underlines the importance of a careful interpretation of the effect of information and on preferences for environmental protection when relying on stated consumption or WTP measures.

The results further suggest a strong positive relationship between the most recent purchasing price for conventional rice and the WTP for organic rice. Considering that the price consumers pay for conventional rice reflects their WTP to pay for rice quality, we could interpret this as a signal that consumers who are willing to pay for higher quality are also willing to pay more for organic food. Based on field observations, examining the quality of rice is indeed a central part of the rice purchasing process.

## 4.7 Conclusion

To our knowledge, this study is the first to assess consumers' willingness to pay for organic rice in Indonesia using an incentive compatible approach. Sufficient local demand is an important precondition to increase adoption rates of organic farming among smallholder farmers. Our results suggest that there are opportunities to promote organic rice among urban and suburban Indonesian consumers. Forty-four percent of the respondents were willing to pay a price equal to or higher than IDR 15,000 (US\$ 1.10), a price farmers commonly ask for organic rice directly purchased at the farm gate, which is not uncommon in Indonesia. Even allowing for a potential desirability bias, which may have inflated bid prices somewhat, this represents a considerable proportion of urban and suburban consumers. This also provides support for the argument that the national government should reconsider its current focus on export markets and provide more support in developing the local market. However, while most respondents (63%) stated that they knew where they could buy organic rice, many of these stated that it was sold in supermarkets. Given that few respondents (8.5%) indicated they were willing to pay the higher prices prevailing in supermarkets this could be an obstacle to the widespread integration of organic rice into consumers' diets. Hence, increasing the availability of organic rice at other retail

outlets and traditional markets, where prices are lower, could enhance the demand for organic rice. More competition could also help to drive down the mark-ups that supermarkets currently apply. Next to the price element, making access to organic products more convenient, i.e. at places where consumers usually shop, could also enhance demand. Srineng and Thapa (2018), for example, found that consumers in Bangkok explain low consumption of organic vegetables with the unavailability of vegetables of choice and the limited number of stores selling organic food. Kini, Pouw, and Gupta (2020) found that the distance to the purchase location negatively correlated to organic demand in Burkina Faso.

Our results suggest that IDR 15,000 (US\$ 1.10) is a threshold price for many consumers in our study area. It should be borne in mind that we used certified organic rice and 88% of respondents stated that certification is important to them. However, obtaining certification is very expensive, especially for smallholder farmers. Currently, many farmer groups that offer certified organic rice receive financial support from the government or other institutions to pay for certification. Without this support, farmers would have to pass on the costs of certification to the consumer and this could decrease uptake. Policy makers are encouraged to continue providing financial support for certification or to reduce the costs for certification with the aim of keeping the price for organic rice at or below IDR 15,000 (US\$ 1.10). Furthermore, alternative labels such as the 'participatory guarantee system' (PGS), which relies on community self-control, could be a promising alternative to facilitate initial market access for farmers.

Both the absence of positive effects of information provision and the positive income effect have further implications for public and private marketing strategies for organic food. As discussed above, the absence of effects of information provision in our study could indicate that short and only basic messages about health benefits are insufficient in further raising consumers' WTP given that most of them already have a basic knowledge of the health benefits of organic food. Further, while other studies (e.g. Rousseau & Vranken, 2013, for Belgium) found that environmental messages seem to be an important driver of demand for organic food, they appear to be of lesser importance in our study context. Given a relatively low level of environmental awareness (demonstrated by responses to the question about pollution in our study), it is questionable whether focusing on environmental benefits is a suitable strategy to raise consumers' WTP for organic food in Indonesia or other lower income countries. However, we found that the WTP of respondents who perceived their exposure to environmental pollution as high was 5% higher, on average, compared to other respondents. We recommend that information provided on health benefits should be more in-depth and detailed than in our study and that consumers should



be sensitized to environmental pollution through agriculture. Sustainability labels could be an important tool in this respect (see e.g. Van Loo et al., 2015).

Finally, we find a strong positive relationship between the most recent purchasing price outside of the experiment and the WTP for organic rice. Since rice prices reflect the quality of rice, this suggests that it is important for organic farmers to use rice varieties that also command a price premium when they are conventionally grown.

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# Appendix

## Appendix A

Table A.4.1: Balance tests

	No Video mean	Environment mean	Health mean	p-value No Video vs. Environment	p-value No Video vs. Health	p-value Health vs. Environment
Female	0.74	0.63	0.74	0.09*	0.98	0.08*
Age	47.13	45.52	44.05	0.39	0.10*	0.41
Married	0.92	0.94	0.91	0.5	0.8	0.35
Muslim	0.86	0.91	0.82	0.26	0.54	0.09*
Years of schooling	12.44	13.1	12.87	0.25	0.41	0.67
Household size	4.06	4.4	4.48	0.14	0.05**	0.69
Income						
Income group 1	0.22	0.26	0.26	0.48	0.48	0.97
Income group 2	0.63	0.51	0.52	0.11	0.11	0.92
Income group 3	0.15	0.23	0.22	0.21	0.22	0.93
Perceived env. pollution	0.24	0.14	0.19	0.08*	0.36	0.36
Past organic rice purchase	0.44	0.57	0.41	0.09*	0.61	0.03**
Last rice purchase price	11,228	11,489	11,613	0.26	0.07*	0.62

Note: \*p<0.10, \*\*p<0.05, \*\*\*p<0.01

**Table A.4.2:** Perceived benefits of organic food consumption across full sample and by treatment arms

	Full Sample	Health Information Treatment Group	Environment Information Treatment Group	No Video Group
Benefits organic consumption				
Healthier (=1)	0.83	0.85	0.80	0.84
Environmentally friendly (=1)	0.05	0.05	0.06	0.04
Quality (=1)	0.06	0.06	0.03	0.08
Better working conditions (=1)	0.01	0.01	0.00	0.03

**Table A.4.3:** Robustness test: Correlates of WTP (OLS) and Consumption Intention (OLS), final vs. full sample

	WTP		Consumption Intention	
	(1) Final Sample	(2) Full Sample	(3) Final Sample	(4) Full Sample
<i>Income (Ref. Income group 1 &lt;IDR 2m)</i>				
Income group 2 (IDR 2m - IDR 5m) (=1)	1,210.42*** (409.18)	1,232.37** (492.15)	-0.00 (0.08)	-0.01 (0.07)
Income group 3 (>IDR 5m) (=1)	2,072.37*** (316.63)	2,452.83*** (408.90)	0.17** (0.07)	0.18** (0.07)
<i>Information treatment</i>				
Health information (=1)	95.95 (335.52)	101.82 (343.63)	0.10* (0.06)	0.08 (0.05)
Environment information (=1)	-127.05 (341.22)	-91.40 (349.75)	0.14** (0.06)	0.11* (0.05)
<i>Socioeconomic characteristics</i>				
Female (=1)	-619.26 (377.00)	-141.86 (427.29)	-0.11** (0.05)	-0.10** (0.04)
Age (in yrs.)	-38.22*** (12.12)	-41.55*** (10.06)	-0.01*** (0.00)	-0.01** (0.00)
Married (=1)	-405.26 (472.06)	-1,003.44 (600.75)	0.20* (0.11)	0.23** (0.11)
Religion (Ref. Muslim)				
Christian (=1)	867.33*** (272.83)	1,098.15*** (297.82)	-0.01 (0.08)	-0.03 (0.07)
Other religion (=1)	-744.27 (709.27)	-1,136.40 (771.19)	0.18 (0.12)	0.17 (0.12)
Years of schooling (in yrs.)	-12.49 (44.50)	43.24 (51.67)	-0.01 (0.01)	-0.01 (0.01)
Household size	-53.20 (133.54)	-53.30 (136.56)	0.00 (0.02)	0.01 (0.02)
<i>Perception of env. pollution &amp; organic consumption</i>				
Perceived environmental pollution (=1)	709.78** (308.75)	582.24* (310.76)	0.02 (0.06)	0.01 (0.06)
Perceived benefits organic consumption				
Healthier (=1)	659.50* (370.03)	708.55* (393.32)	659.50* (370.03)	708.55* (393.32)
Environmentally friendly (=1)	-125.36 (591.24)	-421.92 (491.20)	-125.36 (591.24)	-421.92 (491.20)
Quality (=1)	57.15 (716.37)	29.61 (721.68)	57.15 (716.37)	29.61 (721.68)
<i>Purchasing behaviour and price expectations</i>				
Past organic rice purchase (=1)	608.51** (291.38)	767.98** (287.75)	0.24*** (0.06)	0.25*** (0.05)
Last rice purchase price (IDR)	0.71*** (0.09)	0.38*** (0.09)		
Weekend dummy (=1)	yes	yes	yes	yes
Intercept	6,572.24*** (1,446.53)	9,841.54*** (1,296.62)	0.65** (0.28)	0.60** (0.26)
Observations (N)	293	322	293	322
Adjusted R-squared	0.40	0.36	0.15	0.16

Note: Standard errors are in parenthesis. Standard errors are clustered at the area level. \*p<0.10, \*\*p<0.05, \*\*\*p<0.01

**Table A.4.4:** Robustness test: Correlates of WTP across different specifications

	(1) OLS	(2) Tobit left censored	(3) Tobit bottom and top coded	(4) Tobit interval censored
<i>Income (Ref. Income group 1 &lt;IDR 2m)</i>				
Income group 2 (IDR 2m - IDR 5m) (=1)	1,210.42*** (409.18)	1,507.02*** (469.24)	1,549.46*** (553.80)	1,210.51*** (396.35)
Income group 3 (>IDR 5m) (=1)	2,072.37*** (316.63)	2,326.25*** (346.83)	2,633.92*** (415.64)	2,072.40*** (306.71)
<i>Information treatment</i>				
Health information (=1)	95.95 (335.52)	128.02 (391.84)	-87.40 (342.27)	95.98 (324.99)
Environment information (=1)	-127.05 (341.22)	-75.44 (401.18)	-378.86 (407.13)	-127.04 (330.53)
<i>Socioeconomic characteristics</i>				
Female (=1)	-619.26 (377.00)	-633.39 (388.69)	-778.26* (460.80)	-619.30* (365.18)
Age (in yrs.)	-38.22*** (12.12)	-41.58*** (13.83)	-46.51*** (13.74)	-38.22*** (11.74)
Married (=1)	-405.26 (472.06)	-495.95 (521.75)	-437.37 (631.32)	-405.18 (457.26)
Religion (Ref. Muslim)				
Christian (=1)	867.33*** (272.83)	984.29*** (286.69)	832.66*** (293.22)	867.41*** (264.35)
Other religion (=1)	-744.27 (709.27)	-512.98 (700.84)	-570.21 (798.66)	-744.35 (687.04)
Years of schooling (in yrs.)	-12.49 (44.50)	-18.16 (50.95)	-34.66 (55.79)	-12.48 (43.11)
Household size	-53.20 (133.54)	-60.69 (141.86)	-45.11 (171.82)	-53.21 (129.35)
<i>Perception of env. pollution &amp; organic consumption</i>				
Perceived environmental pollution (=1)	709.78** (308.75)	758.64** (300.40)	791.97** (336.27)	709.84** (299.10)
Perceived benefits organic consumption				
Healthier (=1)	659.50* (370.03)	860.29* (479.87)	1,050.42** (471.35)	659.44* (358.45)
Environmentally friendly (=1)	-125.36 (591.24)	7.44 (647.55)	-108.17 (702.37)	-125.52 (572.69)
Quality (=1)	57.15 (716.37)	157.05 (795.35)	271.56 (874.99)	57.26 (693.89)
<i>Purchasing behaviour and price expectations</i>				
Past organic rice purchase (=1)	608.51** (291.38)	691.14** (309.99)	845.17** (352.45)	608.43** (282.26)
Last rice purchase price (IDR )	0.71*** (0.09)	0.77*** (0.09)	0.91*** (0.14)	0.71*** (0.09)
Weekend dummy (=1)	yes	yes	yes	yes
Intercept	6,572.24*** (1,446.53)	5,561.70*** (1,515.01)	4,202.50** (1,993.80)	6,572.33*** (1,401.12)
Observations (N)	293	293	261	293
Adjusted R-squared	0.40			

Note: Standard errors are in parenthesis. Standard errors are clustered at the area level. \*p<0.10, \*\*p<0.05, \*\*\*p<0.01



**Table A.4.5:** Robustness test: Correlates of Consumption Intention across different specifications

	(1) OLS	(2) OLS without 'maybe'	(3) Probit	(4) Probit marginal effects	(5) Ordered Probit
<i>Income (Ref. Income group 1 &lt;IDR 2m)</i>					
Income group 2 (IDR 2m - IDR 5m) (=1)	-0.00 (0.08)	0.03 (0.09)	-0.01 (0.25)	-0.00 (0.08)	-0.01 (0.18)
Income group 3 (>IDR 5m) (=1)	0.17** (0.07)	0.20** (0.09)	0.73*** (0.28)	0.23*** (0.08)	0.38* (0.23)
<i>Information treatment</i>					
Health information (=1)	0.10* (0.06)	0.10 (0.06)	0.33* (0.17)	0.10* (0.05)	0.25 (0.17)
Environment information (=1)	0.14** (0.06)	0.17** (0.07)	0.46** (0.20)	0.14** (0.06)	0.36** (0.17)
<i>Socioeconomic characteristics</i>					
Female (=1)	-0.11** (0.05)	-0.08* (0.05)	-0.40** (0.16)	-0.13*** (0.05)	-0.17 (0.13)
Age (in yrs.)	-0.01*** (0.00)	-0.01** (0.00)	-0.02*** (0.01)	-0.01*** (0.00)	-0.01* (0.01)
Married (=1)	0.20* (0.11)	0.17 (0.14)	0.68** (0.34)	0.21* (0.11)	0.42 (0.34)
<i>Religion (Ref. Muslim)</i>					
Christian (=1)	-0.01 (0.08)	-0.05 (0.08)	-0.09 (0.26)	-0.03 (0.08)	-0.12 (0.18)
Other religion (=1)	0.18 (0.12)	0.25* (0.14)	0.74 (0.58)	0.23 (0.18)	0.55 (0.49)
Years of schooling (in yrs.)	-0.01 (0.01)	-0.02 (0.01)	-0.05 (0.04)	-0.02 (0.01)	-0.02 (0.03)
<i>Household size</i>					
Household size	0.00 (0.02)	-0.01 (0.02)	0.02 (0.07)	0.01 (0.02)	-0.02 (0.05)
<i>Perception of env. pollution &amp; organic consumption</i>					
Perceived environmental pollution (=1)	0.02 (0.06)	0.03 (0.06)	0.09 (0.21)	0.03 (0.07)	0.19 (0.14)
<i>Perceived benefits organic consumption</i>					
Healthier (=1)	0.19** (0.07)	0.16 (0.10)	0.65*** (0.23)	0.21*** (0.07)	0.34* (0.21)
Environmentally friendly (=1)	0.23* (0.13)	0.28 (0.19)	0.92* (0.50)	0.29* (0.15)	0.25 (0.43)
Quality (=1)	0.14 (0.09)	0.18 (0.13)	0.53 (0.35)	0.17 (0.10)	0.39 (0.34)
<i>Purchasing behaviour and price expectations</i>					
Past organic rice purchase (=1)	0.24*** (0.06)	0.34*** (0.07)	0.85*** (0.23)	0.27*** (0.07)	0.79*** (0.17)
Weekend dummy (=1)	yes	yes	yes	yes	yes
Intercept	0.65** (0.28)	0.57* (0.30)	0.42 (0.89)		
Observations (N)	293	224	293	293	293
Adjusted R-squared	0.15	0.18			

*Note:* Marginal effects for the probit model are calculated at the mean. Standard errors are in parenthesis. Standard errors are clustered at the area level. \*\*\*p<0.01, \*\*p<0.05, \* p<0.10.

## Appendix B

### *Sampling*

We used a two-stage random sampling procedure on the community and household level to select the respondents for this study. In the first stage, we sampled 19 areas in Yogyakarta. Yogyakarta is divided into Yogyakarta City and four regencies, each of which are subdivided into districts (kecamatan). City districts are further subdivided into kelurahans and regency districts into desas. Desas are further divided into smaller units called dusun. The randomisation was undertaken on the kelurahan and dusun level as they are similar in size. To isolate (sub-) urban areas, we excluded all districts that were neither within nor overlapping the area demarcated by the ring road surrounding the city centre. This resulted in a sample of 280 areas, which were then randomised. After physical inspection of the first 30 randomly ordered areas together with local enumerators, areas where agriculture was still prevalent were dropped from the sample. Further, areas in close proximity to universities were dropped as these are dominated by student dorms where students usually have no access to cooking facilities and most food is ordered. This procedure resulted in 19 remaining areas which we selected as study areas.

In the second stage, households were randomly selected by enumerators, who set out from a mosque in a randomly assigned direction. From thereon, every third household was approached. Naturally, not all approached households participated.<sup>4</sup> In these cases, the next third household following the non-participating household was approached. Initially 322 respondents participated in the experiment and subsequent interview. However, some respondents revealed characteristics or behaviour that might bias WTP estimates and therefore these respondents were dropped from the final sample. In total 29 respondents were dropped.<sup>5</sup> After the exclusion of these respondents, 293 observations remained and were included into the final sample for data analysis.

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<sup>4</sup>The most frequent reason for a refusal to participate was that the household member responsible for food shopping was not at home. However, in some cases, households even refused to participate if this person was present.

<sup>5</sup>Seven respondents were excluded from the study because they refused to buy the organic rice after winning the bidding game. Eight respondents were excluded as their comments showed that they did not reveal their true WTP in the experiment. Three respondents reported that they already bought organic rice regularly. They were excluded because their bids, informed by knowledge of the real price, probably do not reflect their real WTP as they might tend to not offer prices higher than the real price they usually pay for organic rice. Finally, eleven respondents said they received rice from Raskin, a government programme that distributes free rice to households considered very poor. They were excluded from the study as it was considered they would not buy organic rice outside of the experiment because of their severe financial constraints.



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