# Forest change and agricultural productivity: Evidence from Indonesia

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**Abstract**

We examine the effect of forest cover change on agricultural productivity using household panel data and remote sensing data on forest change. The focus of the study is rural Indonesia, where deforestation is causing intensive biodiversity loss while agriculture is the main industry. We estimate an agricultural production function and find that farmers in rural Indonesia experienced a reduction in agricultural productivity of 45% between 2001 and 2014 or US$2.63 billion in 2014. In addition, we explore the mechanisms underlying the productivity loss and find that biological pest control is the most plausible explanation.

# 1 Introduction

Forest ecosystem services benefit human society through their environmental and social effects such as food production, recreation, nutrient cycling, and climate change mitigation (Costanza et al., 1997, 2017; Millennium Ecosystem Assessment (MEA), 2005; TEEB Foundations, 2010). While such roles are recognized, deforestation remains an important issue, particularly in the tropics and African countries (FAO, 2015; Kim et al., 2015; Sloan and Sayer, 2015). This has resulted in serious economic damages associated with the degradation of direct and indirect forest ecosystem services (Costanza et al., 2014).[1] The economic value of direct ecosystem services (i.e., the direct use value) has been assessed in various ways, such as the effect on market prices. For example, forest income represents, on average, 22 to 60% of total household income in developing countries (Vedeld et al., 2007; Angelsen et al., 2014; L'Roe and Naughton-Treves, 2014). In contrast, there is limited assessment of the indirect economic value of ecosystem services (i.e., the indirect use value) or the internalizing of externalities. Typically, forest conservation policies consider the price the function of carbon storage in forests.[2] However, other functions of ecosystem services are not included as monetary values in conservation policies. Therefore, forest conservation policies have not considered ecosystem services in terms of monetary value.

This study empirically attempts to quantify the externality of forests in terms of agricultural productivity. Specifically, we examine how agricultural productivity is affected by a change in forest coverage in rural Indonesia

[1] Costanza et al. (2014) estimated the global value of forest ecosystem services to be US$ 16.2 trillion to US$ 19.5 trillion in 2011.

[2] For example, the Reducing Emissions from Deforestation and Forest Degradation plus (REDD+) mechanism considers payments for forest conservation, a type of payment for ecosystem services (PES) for forest conservation and the amount of carbon emissions that are avoided in conserved areas.

by combining longitudinal household panel survey data and remote sensing data of forest cover change for the targeted years 2000, 2007, and 2014. An empirical challenge is that agricultural productivity might be heterogeneous in households with or without deforestation. Therefore, we regress agricultural yield per planted area for regional forest cover along with year and household fixed effects as well as other household and regional characteristics. Since household fixed effects are controlled, the effect of forest cover is identified by within-household variation in the change in forest cover.

The economic literature has paid little attention to the forest externality for agricultural productivity although considerable ecological evidence shows that forest biodiversity affects agricultural yields and productivity.[3] Quantifying the externalities of forests and the effect on agriculture is important for the following three reasons:

First, the existence of positive forest externalities might help to close the gap between payment and agricultural revenue in forest conservation policies. For forest conservation policies, payment for forest conservation tends to be lower than agricultural revenue.[4] These gaps are often wide in the case of large plantations such as oil palm plantations (Butler et al., 2009). Failure to quantify forest externalities potentially underestimates the value of forests, resulting in delayed conservation policy implementation (Olbrei and Howes, 2012).

Second, improving agricultural productivity is important for poverty alleviation in rural Indonesia. The majority of the poor in Indonesia live

[3] Recently, studies on the economic value of forest ecosystem services have increased, and many studies have assessed climate regulation, water flow regulation, and recreation as the indirect use value of forest ecosystem services (de Groot et al., 2012; Costanza et al., 2017).

[4] For example, in REDD+, payment for conservation relies on the carbon price and is considered compensation for the forgone chance of agricultural development.

in rural areas, and they mainly engage in low-productivity agriculture (Aji, 2015) while recent economic growth has reduced poverty. For example, the farmers who have not benefited from forest development, such as the establishment of oil palm plantations, might engage in small-scale agricultural work. Therefore, potential agricultural loss due to forest cover change might affect farmer welfare, particularly in rural areas. In rural Indonesia, agriculture employs more than 70% of the labor force (McCulloch et al., 2007). Therefore, examining the effect of change in forest coverage on agricultural productivity using rural household data is an important contribution to the literature on rural development and the elimination of rural poverty.

Third, the empirical evidence of this study is based on actual farming data that have not yet been considered. While ecological studies have appreciated the role of ecosystem services in agricultural outputs, these studies have a common shortcoming in that their analyses rely on an experimental approach. Thus, whether forest ecosystems can improve agricultural output in practice remains under discussion in ecological studies. Quantifying the effects of forest ecosystem services on agricultural productivity using practical agricultural data is important to inform the debate on the role of natural habitats.

Our estimation results suggest that a boost in households' agricultural productivity is a response to increasing forest cover in subdistricts. The results are obtained after controlling for household and subdistrict characteristics. In addition, these results remain robust when the sample is restricted to rice farmers, while we find no significant effects when the sample is restricted to some perennial estate crop farmers and non-farming business income. This could support the existence of biological interaction between forest species and agricultural pest insects or biological pest control. Further, we investigate the effect of forest cover on household welfare with respect to differences in the expenditures of farmers. We find that forest cover change negatively affects the non-food expenditures of rice farmers, which is consistent with the lower productivity observed in deforestation areas. On the other hand, we find no difference for expenditure on any goods in non-farming households and perennial estate crop farmers. This is consistent with our results.

The remainder of this paper is as follows. Section 2 presents the ecological mechanism of forests and agriculture through a literature review. Section 3 describes the dataset and empirical model. Section 4 presents the empirical results, which provide evidence of a positive forest externality on agricultural productivity, but no evidence of forest extent externality on tolerant tree farmers and non-farming households. Section 5 concludes.

## 2 Literature review

Forest ecosystem services can be broadly classified into direct and indirect use values (Gregersen et al., 1995). The direct use values are quantified by food security and livelihood through the provision of forest services, for example, the production of food (Arnold et al., 2011; Powell et al., 2013; Ickowitz et al., 2014; Pingali, 2015), timber (Singh et al., 2010), and non-timber forest products (Mugido and Shackleton, 2018).

The indirect use values are assessed according to non-market goods such as controlling water flows, preventing soil erosion, offering pollination habits, and enhancing pest control. We review the ecological studies that analyze the impact of indirect forest ecosystem services on agriculture to clarify the research gap and the aim of this study.

Forest ecosystem services affect agricultural output in several ways including soil conservation (Mäder et al., 2002;), nutrient retention (Raudsepp-Hearne et al., 2010), and crop pollination (Klein et al., 2003, 2007; Ricketts et al., 2004; Carvalheiro et al., 2010). Mäder et al. (2002) found that organic agriculture enhanced soil fertility, and greater biodiversity resulted in less dependency on chemical inputs. With respect to nutrient retention in soil, Raudsepp-Hearne et al. (2010) identified 20 ecosystem services based on spatial land-use patterns and found that, in Canada, soil fertility in terms of phosphorus retention is positively correlated with the forest cover rate. Emphasizing crop pollination, Klein et al. (2003) identified the factors influencing pollination and found that the number of pollinators (social bees) decreased with increasing distance between the forest and the coffee plantation. Similarly, Carvalheiro et al. (2010) found that the distance to a natural habitat is associated with the number of flying pollinators while ants were not affected. Ricketts et al. (2004) conducted pollination experiments in Costa Rica and found that forest-based pollinators can increase yields and the quality of coffee beans by reducing failures in production. These pollinators in natural habitats contribute to agricultural production. Klein et al. (2007) found that over 75% of the world's important food crops increased yields with natural pollinators.

Notably, according to numerous ecological studies, pest control has provided agricultural benefits (Pimentel, 2005; Bianchi et al., 2006; Bátray et al., 2011; Chaplin-Kramer et al., 2011; Thies et al., 2011; Blitzer et al., 2012; Karp et al., 2013; Shackelford et al., 2013; Milligan et al., 2016; Rusch et al., 2016). This mechanism is referred to as biological control, or biological pest control, and is defined as the use of an organism to reduce the population density of another organism. A natural habitat has a higher population of natural enemies, leading to enhanced pest suppression to reduce the possibility of crop damage. Pimentel (2005) found that the contribution of biological control is estimated to be 50 to 90% of total pest control.[5] Bianchi et al. (2006) reviewed ecological studies that used a field experiment approach and found that many studies have concluded that landscape complexity is associated with a higher population of natural enemies and lower pest pressure in agricultural fields. Chaplin-Kramer et al. (2011) conducted a meta-analysis and found that the population of natural enemies has a positive response to landscape complexity. The authors also found that the range of habitat effects differs depending on the enemy types. Thies et al. (2011) conducted field experiments in Europe and found that large areas of natural habitat mitigate pest damage in agricultural fields through greater control of cereal aphids. Blitzer et al. (2012) found that natural enemies move from natural habitats to agricultural fields and discussed the potential of inverse effects, whereby natural enemies move from agricultural fields to natural habitats. Bátray et al. (2011) found that surrounding habitats play a role in determining on-farm biodiversity and particularly influence the bird population. Karp et al. (2013) conducted field experiments in coffee plantations in Costa Rica and found that forest-based birds reduced insect pest damage to coffee beans by up to 50%. Shackelford et al. (2013) conducted a meta-analysis of field studies and found that both natural enemies and pollinators are likely to respond to natural habitat complexities. In addition, the authors found that landscape complexity has significantly stronger effects in non-woody crops and annual crops compared to woody crops. Milligan et al. (2016) found that pest pressure in coffee plantations was influenced by agricultural management and its surrounding

[5] Pimentel (1988) found that pesticide inputs and host-plant resistance account for the remainder of pest control (10 to 50%).

habitats. In Kenya, the authors found that pest suppression was positively associated with the surrounding tree canopy and negatively associated with the distance to forest areas. Rusch et al. (2016) conducted a field experiment in Sweden and found that pest control increased with landscape complexity. Pest control decreased with distance or the proportion of natural habitat at spatial scales.

Based on the field experimental approach, many ecological studies have found that natural habitats have the potential to affect agricultural yields positively through biological control. The proximity, largeness, and heterogeneity of natural habitats are considered important factors that enhance biological control efficiently. On the other hand, Tscharntke et al. (2016) argued that natural habitats can fail to enhance biological pest control in actual fields. They identified some conditions under which natural habitats cannot increase agricultural output. For example, when forests offer a habitat for pest insects rather than their predators, natural habitats create agricultural loss. Thus, the effects of natural habitats on practical farming are still unclear and should be examined.

The conversion of primary forest is leading to severe biodiversity loss in Indonesia.[6] In recent decades, forest cover change in Indonesia is closely related to the rapid expansion of oil palm plantations. Indonesia and Malaysia account for 87% of global oil palm production, and plantation areas increased from 3.5 Mha in 1990 to 12.9 Mha in 2010 (Gunarso et al., 2013; USDA, 2014). This rapid forest development caused severe biodiversity degradation. By using data on bird and butterfly diversity, the estimated biodiversity loss due to conversion of either primary or secondary forests

6 The primary forest loss in Indonesia is likely to overtake that of Brazil: annual primary forest loss was estimated to be 0.84 million hectares (Mha) for Indonesia and 0.46 Mha for Brazil in 2012 (Märgono et al., 2014).

to oil palm plantations is estimated to be 73% to 83% in Indonesia (Koh and Wilcove, 2008; Koh et al., 2011). Birds are considered an important player, or natural enemy, in biological pest control to suppress insect pests because more than 50% of species are predominantly insectivorous (Koh and Wilcove, 2008; Wenny et al., 2011; Karp et al., 2013). Recent studies focusing on the impacts of oil palm plantations on socioeconomics found that oil palm plantations improve local living standards in areas such as nutrition, expenditure, and wealth accumulation (Euler et al., 2017; Gatto et al., 2017). However, the negative effects of biodiversity losses on local farmers through ecological mechanisms require assessment to determine the economic impact of forest development.

# 3 Data

## 3.1 *Forest cover data*

The data on changes in forest cover were obtained from satellite observations provided by Hansen et al. (2013). The dataset has been updated, and the latest edition is available for the period from 2000 to 2017.[7] The data are a compilation of records on global forest loss and extent at a spatial resolution of 30 meters (m) obtained from multi-spectral satellite images. A pixel with vegetation higher than 5 m is reported as the forest extent in 2000.[8] In addition, the data set reports that the pixel experienced forest loss (i.e., vegetation has been cleared in the pixel) in each year during the period 2000 to 2017. This data set allows us to estimate the amount of forest cover of our

[7] See the website: https://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.4.html. Although the 2000 to 2017 data on forest extent and loss are available, the authors suggest that users should cite "Hansen et al., 2013" for the data.

[8] This might include perennial estate crops such as oil palm, rubber, and coffee plantations established before 2000.

considered administrative area and period (subdistrict level for the targeted years 2000, 2007, and 2014).[9]

We first aggregate the forest extent of every pixel ($Extent_j$) and the loss ($Loss_{jy}$) for pixel $j$ for each year $y$ ($y = 0; 2000, ...y = 14; 2014$) for every subdistrict ($s$, with N pixels inside its borders) area. $Extent_j$ denotes the forest extent in 2000, taking one if the pixel shows the forest extent more than 10% and zero otherwise. $Loss_{jy}$ denotes the forest loss for each year from 2001 to 2014 $y$, taking one if the pixel experienced forest loss in a corresponding year and zero otherwise. $Fcover_{st}$ denotes the forest cover rate in subdistrict $s$ for year $t$ ($t = 0; 2000, ...t = 14; 2014$) .[10] Because our household data contain the place where households settle at the subdistrict (*kecamatan*) level, we average the forest cover rate by dividing the forest cover by area at the subdistrict level. We consider a pixel with more than 10% of tree cover as a forest.[11] Then, the forest cover rate for the subdistrict and for the year is estimated as follows:

$$Fcover_{st} = \frac{1}{N}\sum_{j=1}^{N}\sum_{y=0}^{t}(Extent_j - Loss_{jy}), \quad if \quad (Extent_j, Loss_{jy} \in \text{subdistrict}_s) \quad (1)$$

We do not consider forest gain when calculating forest cover. The data set reports the pixels in which vegetation gain has occurred. However, a pixel with vegetation gain is defined as a place with vegetation of 5 m or higher and where a forest has already been lost or originally did not exist. For example, a pixel where a plantation or agricultural field has been established

9 As we explain in the next subsection, we need to combine forest cover data with three years of our socio-economic outcome data (for 2000, 2007, and 2014). To combine these data, we calculate the forest cover rate for 2000, 2007, and 2014 using the pixels of forest extent in 2000 and pixels of forest loss in each year.

10 Note that when $t = 0$, $Fcover_{st}$ is equal to $Extent_j$ because the value of $Loss_{jy}$ is zero.

11 The data set offers information on the pixel with tree cover of 0 to 100%.

after clearing forest would be defined as a forest. Thus, including the gain in the calculation could lead to confusion regarding the agricultural area and forest. To avoid this problem, we consider only primary forests as forest area.

Figure 1 shows the change in forest cover in Indonesia between 2001 and 2014. Figure 2 shows that Kalimantan and Sumatra account for a large part of deforestation in Indonesia during the study period.

Note that we classified land-use type into forest and non-forest based on the pixels. More detailed classifications are likely to be employed in geographical studies to clarify the land-use and land-cover condition. For example, Ekadinate and Vincent (2011) classified six land-use types (natural forest, rubber plantation, oil palm plantation, shrub, rice fields, and settlement area) to identify the landscape in Sumatra, Indonesia by using remote sensing data.[12]

## 3.2 *Household panel data and merged dataset*

The household-level data we employ are from the three recent waves of the Indonesian Family Life Survey (IFLS), a continuing longitudinal household survey. The IFLS surveys were conducted in 1993 (IFLS1), 1997 (IFLS2), 2000 (IFLS3), 2007 (IFLS4), and 2014 (IFLS5). The survey covers 13 of the 26 provinces covering 83% of the total population in Indonesia. The low attrition rates are an advantage of the IFLS surveys; 86.9% of households that participated in the IFLS1 in 1993 were re-interviewed in the IFLS5 in 2014. The survey contains information on agricultural inputs, outputs, and characteristics of households.

Table 1 reports the mean of variables by year and farming type. We

[12] An alternative method is to obtain geographical information from field surveys. Gatto et al. (2015) quantified how socioeconomic factors and policy are associated with land-use change combining geographical and socioeconomic information from village surveys.

employed data from IFLS3 (2000), IFLS4 (2007), and IFLS5 (2014). The agricultural outcomes considered in this study are the agricultural revenue per planted area of each household. The variables affecting agricultural outcome include land size, number of workers, farming assets, age, gender, and educational attainment of household head. We also consider a community-level outcome, GDP per capita in the province. The data are provided in real terms using deflators in spatial variations in prices.

The main agricultural produce of households is reported in the data. The produce can be categorized as perennial crops, such as rubber, sugar cane, wood, coffee, tobacco; annual crops including rice, corn, cassava; and livestock such as goat, chicken, pig, and fish.

The data set contains agricultural output for 3,259 farmers excluding livestock farmers. The logarithm of real agricultural revenue increased from 14.054 Indonesian rupiah (IDR) in 2000 to 14.722 IDR in 2014. This increase is driven by the growth of revenue among non-rice farmers from 13.956 IDR in 2000 to 14.746 IDR in 2014. Household heads' average age increased from 47.02 years in 2000 to 52.37 years in 2014. This is because of the continuing longitudinal survey.[13]

The share of rice farmers decreased dramatically from 50.4% in 2000 to 41.3% in 2014 as more Indonesian farmers started producing crops other than rice. The number of farmers did not decrease during the period.

To merge the forest cover subdistrict-level data with the households' socioeconomic data, we refer to the information from the specific subdistrict where the household was located each year. IFLS provides the place where the households settle at the province, district, and subdistrict levels. Note that we compiled forest cover data based on boundaries at the

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[13] New households that split from the original household respondents were interviewed in IFLS4 and 5.

subdistrict-level and year preceding the IFLS interview.

We restrict the sample to households that did not live in provinces on Java island (provinces of Jawa Barat, Jawa Tengah, Jawa Timur, and Yogyakarta) as well as households that engage in self-employment agricultural activities. We attempt to examine how forest cover change can affect agricultural productivity in rural areas. We then restrict the sample to provinces that experienced forest losses. This restriction is applied because four provinces had very little or no forest cover change during the study period. In addition, the heterogeneity in landscape composition and agriculture between Java and other islands is substantial. Margono et al. (2014) noted that the rate of primary forest, including intact and degraded forest, in Sumatra (34.3%) and in Kalimantan (56.8%) are much more abundant than in Java and Bali islands (0.04%) in 2000. This may mean that our forest data, *Fcover*, captures a different land composition in Java and other islands. For example, *Fcover* for Java island is likely to include agricultural plantations while *Fcover* for Sumatra and Kalimantan, it includes primary and secondary forests. For agriculture, the number of households engaging in agriculture decreased by 23.4% in Java and Bali islands while it decreased by 2.3% in other islands from 2003 to 2013 (BPS, 2013). These data also imply that the role of agriculture may be different in these islands. They would also lead to biases in estimates if we include Java island in the estimation.

## 3.3 *Model*

We analyze the effects of changes in forest cover using a regression model. Consider the following model:

$$\ln Y_{ist} = \beta_0 + \beta_1 Fcover_{st} + \beta_2' X_{ist} + \theta_i + \zeta_t + \epsilon_{it}, \tag{2}$$

where $Y_{ist}$ is the agricultural value of yield for a plot (revenue per planted area) in household $i$ in subdistrict $s$, $Fcover_{st}$ is our measure of forest cover in subdistrict $s$ and year $t$; that is, the rate given by the ratio of forest area to the subdistrict dimension in which household $i$ settles in interview year $t$. $X_{ist}$ is a vector of observed household and regional characteristics, $\theta_i$ is household fixed effects, $\zeta_t$ is year fixed effects, and $\epsilon_{it}$ is an error term that is not correlated with other variables. In Equation 2, $t$ can be taken as 0, 7, and 14 corresponding to 2000, 2007, and 2014, which are the years preceding the IFLS interview. The household fixed effects capture unobserved household and regional characteristics including traditional family procedures in agriculture and historical forest status in the area. The year fixed effects capture factors that affect agricultural output equally across households. For instance, improvements in agricultural technologies in Indonesia and changes in industrial structure are included in the year fixed effects.

# 4 Results

## 4.1 *Forest cover change and agricultural production*

The results of household and year fixed effect estimation are shown in Table 2.[14] We run the Hausman specification test, and the value of the Hausman test ($p$-value = 0.000) shows that the fixed effects (FE) specification is preferred compared to the random effects in our models. In column (1), we explore the relationship between agricultural productivity and forest cover without controlling for household inputs and characteristics. We then include in household characteristics and GDP per capita at the province level in the

[14] In addition, we control for subdistrict (*kecamatan*) fixed effects rather than household fixed effect in Table A1. There are no significant differences in the effects of forest cover. The coefficient of *Fcover* is 3.418 and statistically significant at the 1% level.

regression as shown in column (2). As a reference, column (3) reports the estimation result using the interaction between a dummy of farmers settled in Sumatra or Kalimantan and a year trend of 2014 as a proxy for $Fcover$. In this specification, the coefficient of the Sumatra and Kalimantan dummy can be interpreted as the average change in Sumatra and Kalimantan relative to other islands.[15]

In addition, we estimate a two-stage least squares (2SLS) regression using lagged forest cover data as an instrumental variable.[16] The result is presented in column (4) in Table 2. The effects of forest cover remain, but the magnitude decreases in the instrumental variable (IV) estimation. The coefficient of $Fcover$ is 2.241 and statistically significant at the 10% level while, in the FE estimate, it is 3.671 (column 2). We test the disparity of the FE and the IV results using the Durbin-Wu-Hausuman (DWH) test. The $p$-value from this test is 0.669. We fail to reject the exogeneity null of $Fcover$ even at the 10% significance level, indicating that the ordinary least squares (OLS) estimate is consistent. The IV result thus supports our FE result of a positive and statistically significant effect of forest cover change on agricultural yields. In light of the DWH test result, we rely on the FE specification in the remainder of the manuscript since it is more efficient.

Our variable of interest, *Fcover*, shows that there is a significant positive

[15] Figures A1 and A2 show the change in forest cover and agricultural output between 2000 and 2014. Sumatra and Kalimantan experienced large-scale forest loss of approximately 10 percentage points between 2007 and 2014. In addition, growth in agricultural output in Sumatra and Kalimantan slowed between 2007 and 2014.

[16] Because the forest cover data before 2000 does not exist, we use forest cover data for the years from 2000 and 2007 to estimate the production function for the years 2007 and 2014. The result of the first stage of the 2SLS estimation is presented in column (1) in Table A3. The $F$-statistics for the excluded instrument in the first stage is 46969.92, which indicates that our instrumental variable is not weak.

impact on agricultural productivity in every estimation.[17] This finding indicates that the amount of forest has the potential to affect agricultural productivity positively. In other words, this result confirms the existence of positive externality of forests on agricultural output.[18] The results are consistent with the findings from the ecological literature on a positive relationship between natural habitat and agricultural outputs (see Section 2).

Among agricultural inputs, *labor* and *assets* have a positive effect on productivity. *Land* has a negative sign, which indicates that agricultural productivity decreases with increasing plot size. This inverse relationship between land productivity and farming size is known as inverse productivity and has been observed in many developing countries (Larson et al., 2014). To check the endogeneity of labor input in estimating agricultural production functions, we estimate a 2SLS regression using input endowments of the number of household members as instruments for labor input (the number of working-age members).[19] It is possible that forest loss affects agricultural output through change in local labor demand. For instance, the expansion of agricultural plantations in the forest area increases demand for local agricultural labor. Then, forest loss could lead to reduced labor input for household farming activities.

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[17] In column (3), the coefficient for Sumatra and Kalimantan in 2014 has a negative sign. This result supports our finding of a positive relationship between forest cover and agricultural output.

[18] We confirm that the results are robust if households who mainly engage in livestock are included in the estimations (the results are presented in columns (1) and (2) in Table A2). On the other hand, we found that the coefficients of *Fcover* are statistically insignificant for households that live in Java island. The results are presented in columns (3) and (4) in Table A2. This is because there are substantial differences between Java island and other areas in terms of forest and agriculture that we explained in subsection 3.2.

[19] The result of the first stage of the 2SLS estimations is presented in column (2) in Table A3. The $F$-statistics for the excluded instrument in the first stage is 847.12, which indicates that our instrumental variable is not weak.

The variable *rice farmer* is a dummy variable that takes one when the farmer produces rice as a main product and zero otherwise. The coefficient of *rice farmer* is negative but statistically insignificant indicating that there is no difference between rice and other crops in terms of productivity. This reflects that rice is still an important crop for farmers in rural Indonesia. In fact, rice is the most-produced main crop (41% of farmers) followed by rubber (8.4%), corn (6.3%), and cassava (3.5%).

We find that *GDP per capita* significantly decreases agricultural productivity. This might reflect the change in labor supply for agricultural and other work. Once regions are developed, the labor force tends to be reluctant to perform agricultural work.

## 4.2 *Cost of deforestation on agricultural production*

The magnitude of the effect is important for forest management policies. The coefficient of *Fcover* in column 2 in Table 2 is 3.671 indicating that a 1% reduction in deforestation increases productivity by approximately 3.7% in the region. Using this result and the historical deforestation trend, the total agricultural loss in Indonesia due to deforestation is estimated to be 45% between 2001 and 2014 or US$2.63 billion in 2014.[20]

This result takes into account that economic returns to agriculture could help to mitigate the conversion of forest to new agricultural land. According to the Bureau of Statistics Indonesia (BPS) (2016), approximately 1.8 MHa was newly cultivated as agricultural land between 2001 to 2014 in Indonesia except for Java island.[21] Multiplying the average revenue, the revenue from

[20] The deforestation rate and agricultural production growth in Indonesia were 13.1% and US$ 5.5 billion, respectively, between 2001 and 2014. Then, the total agricultural loss can be obtained by multiplying 0.131 by 0.037 by US$5.5 billion.

[21] We aggregated the new agricultural land for rice, maize, cassava, mung bean, peanut, soybean, and sweet potato between 2001 and 2014.

these new cultivated areas is estimated to be approximately US$1.05 billion. Because the average agricultural loss due to deforestation is US$2.63 billion, the return from forest conservation would be around 250%. Thus, forest conservation proves to be highly cost effective.

## **4.3** *Biological pest control versus other mechanisms*

Our main results suggest that forests have a positive externality on agricultural productivity. However, as discussed in Section 2, forests have the potential to affect agricultural output in several ways such as biological control, soil conservation, nutrient retention, and crop pollination. In addition, forest loss could occur alongside forest fires in Indonesia, with damage to both forests and agricultural land. To explore the likely channels driving the relationship between forests and agriculture, we restrict the samples based on cultivated crop types in the estimation of the production functions and estimate the effects of forest cover for annual crop farmers, vulnerable tree farmers, and tolerant tree farmers.

A difference between annual crops (including rice) and perennial crops is their susceptibility to pest insects through their life cycles. According to Coley et al. (1985), the strength of plants' defenses against herbivores is related to their growth speed. Fast-growing species show less defense against pests than slow-growing species, which implies that annual crops might be more vulnerable to pests than perennial estate crops. In addition, perennial crops can be classified into vulnerable and tolerant trees. Vulnerable trees mainly consist of fruit-bearing trees. Typically, pest insects might severely damage the fruit or crop and affect the viability of the trees. Thus, tolerant trees are less susceptible to pest damage than annual crops and vulnerable trees.[22]

Table 3 presents the estimation results by farmers' crop types: column (1) for rice; column (2) for annual crops (including rice); column (3) for vulnerable tree crops; and column (4) for tolerant tree crops.[23] The coefficients of *Fcover* are positive and statistically significant for rice, annual crops, and vulnerable tree farmers while the coefficients of forest cover for tolerant tree farmers are statistically insignificant. These results imply that biological pest control is likely be a factor in the relationship between forests and agricultural outputs. Because ecosystem services other than biological control, such as water, should affect agricultural output regardless of crop type, the effects should be found in other types of crops. The difference between rice and estate crops is their susceptibility to pest insects.

Similarly, if forest fires could damage entire agricultural areas and forests, then the effect should be found not only in rice but also in estate and livestock. We argue that a plausible channel of this relationship is biological control through forest diversity.

### 4.4 *Placebo test for non-agricultural income*

Since the forest cover change does not occur randomly, it is possible that our results suffer from omitted variable bias. For instance, there might be unobserved variables that influence both regional income and forest cover change. We test for omitted variable bias by applying the estimation to non-farming income, which is unlikely to be associated with forest cover change. If other latent factors were related to the effects of forest cover change, then forest cover change would be related to income from

[22] Table A4 shows the classification of crops in our estimates.

[23] The restriction is performed according to the type of crop that the farmer cultivated as a main crop.

non-farming business also.

The test sample is composed of $3,369$ households that engage in non-farm family business. The descriptive statistics for non-farming business households are presented in Table A5. The dependent variable is household income from non-farming business. The explanatory variables include household and year fixed effects as well as household characteristics such as age of head, education of head, and family size. Column (4) in Table 3 presents the results of the placebo test. The coefficient for forest cover rate is statistically insignificant. This result offers support for our identification strategy.

## 4.5 *Attrition and household re-composition biases*

Since farmers could stop farming by decreasing output, the effects of forests could cause sample attrition bias. In addition, as mentioned above, our estimates include split-off households that are observed as new households for the survey rounds of 2007 and 2014. There is possible bias if the variables of these new households are associated with forest cover change in the region. To check if the sample attrition and re-composition are systematically related to the forest change, we restrict the sample to strongly longitudinal data. We first report our main result in column (1) in Table 4. The coefficients of forest cover decreased from those of our main results (in column (1)) but are still statistically significant at the 1% level.

This result suggests the possibility that our main results underestimate the effect of forest cover change on agricultural productivity. If farmers who stop farming have a serious effect on agricultural productivity, then the estimation results on farmers who continue to farm would be biased.

## 4.6 *Change in household strategy*

An alternative explanation for lower levels of agricultural productivity is related to the farming strategy of households such as farming land size and assets. If farmers change farming plot size or assets in response to converted forest, then productivity changes.

Table 5 shows the results. We find no increase in land size and farming assets in response to changes in forest cover. This result indicates that the change in productivity is driven not by household strategy but by changes in forest cover.

## 4.7 *Effects on household consumption*

Our estimation results show the link between forest cover and agricultural productivity. We expect that changes in forest cover subsequently lead to changes in living standards such as household consumption. It is possible that the effects could be averted. For example, plantation companies that are typically established in cleared forest areas employ local workers and improve the local economy (Gatto et al., 2017).

To examine this issue, we regress *household consumption* on *forest cover*. The results are presented in Table 6. The coefficient of *forest cover* on food consumption (column (1)) is positive but statistically insignificant, while the coefficient on non-food consumption (column (2)) is positive and statistically significant. The sample of these two models consists of rice farmers, whose productivity is strongly affected by forest cover change (see Table 2). These results reflect the fact that income elasticity of non-food demand is higher than that of food demand.

In addition, we restrict the sample to households engaging in estate crops, livestock, and non-farming business (the results are reported in columns (3), (4), and (5) in Table 6, respectively). Note that the agricultural productivity of these households is not affected by forest cover change (see Table 2). *Fcover* also has no significant effect on either food or non-food consumption.

# 5 Conclusion

This study examines an important externality that forest cover loss might impose; that is, reducing agricultural productivity. We find robust evidence that agricultural productivity has decreased due to forest cover losses. The reduction is economically significant at a decline of approximately 45% or US$2.63 billion in mean production between 2001 and 2014.

In addition, we find that biological control seems to be a plausible mechanism between forest and agricultural productivity. Rice, fruit, and vegetables are relatively susceptible to insect damage compared to estate crops such as rubber, sugar, wood, and livestock.[24] Rice crop loss due to pest damage is reported to be 95% at maximum (Teng et al., 1990). On the other hand, the rubber tree is not seriously affected by pest insects.[25] If other mechanisms of the forest ecosystem, such as water, soil, and forest fires, are related to productivity, then the effect of forest cover change might be observed in both the rice and estate farmer estimations.

These findings have important implications for environmental and development policies. In particular, the results suggest that forest conservation policies should consider the externalities of forests on agricultural productivity and farmers' welfare. In Indonesia, the use of pesticides has been subsidized by the government to control rice pests.

[24] For example, rice is reported to be a host plant of more than 800 insect species (Dale, 1994). Every part of the rice plant is exposed to these pest insects (e.g., root, stem, leaf, and grain) and at every growth stage (e.g., seedling, matured) (Dale, 1994).

[25] There are few reports of pest damage to rubber trees because insect pest attacks on rubber trees are mostly sporadic and localized (Jayarathnam, 1992).

However, the use of pesticide has killed more natural predators than pest insects, thereby removing the enemies of pests. This lack of enemies has resulted in significant pest damage to crops. The loss of rice production has affected farmers' livelihoods and is estimated to be valued at US$ 100 million in Indonesia (Settle et al., 1996; Tscharntke et al., 2016). Therefore, it is essential that policymakers pay significant attention to the conservation of forest ecosystems rather than the expansion of pesticide usage to improve the livelihood of farmers.

The potential costs from lost crop production are neglected in forest conservation policy, which usually focuses on the trade-off between agriculture and conservation. Our results suggest that forest conservation could improve the living standards of local farmers. Using the result, the average annual loss due to the change in forest cover is estimated to be US$2.56 billion between 2001 and 2014. This loss offsets the benefits from agricultural expansion in forest conservation policies.

Finally, several limitations of this study should be mentioned. First, we cannot clearly determine the mechanism between change in forest cover and agricultural productivity. Although we run several robustness checks, it is possible that mechanisms other than biological control could affect productivity, such as the quality and nutrients of soil, water, and forest fires. Similarly, we cannot examine in detail the changes in farmers' decisions on agricultural production that are affected by forest cover changes. For example, farmers could change their agricultural behavior or investment in response to change in forest income. Second, we cannot examine the detailed effects of different land-use types on ecosystem services due to a lack of land use data. The forest cover data we employed includes forest extent and perennial estate crops such as oil palm, rubber, and coffee plantations. The decline of forest cover might include biodiversity loss from both deforestation and plantation destruction. Therefore, there is a possibility that our estimates underestimate the effects of forest cover change on agricultural outcomes through biological pest control because the level of biodiversity on agricultural plantations is considered less than that in forests (Koh et al., 2008). Third, several household and community-level variables to control for agricultural outcome are excluded from our models because of data limitations. Therefore, we cannot fully rule out the possibility of bias that households' unobserved characteristics or strategies explain a part of the reduction in agricultural productivity. For example, we omit household's technological adaptation such as pesticide input. Households' choices of pesticide use may be associated with the pest condition of their agricultural fields. Unfortunately, information on pesticide is not available on IFLS. Future studies should attempt to address these issues.

# Acknowledgment

This work was supported by JSPS KAKENHI Grant-in-Aid for Young Scientists (B) 16K17127.

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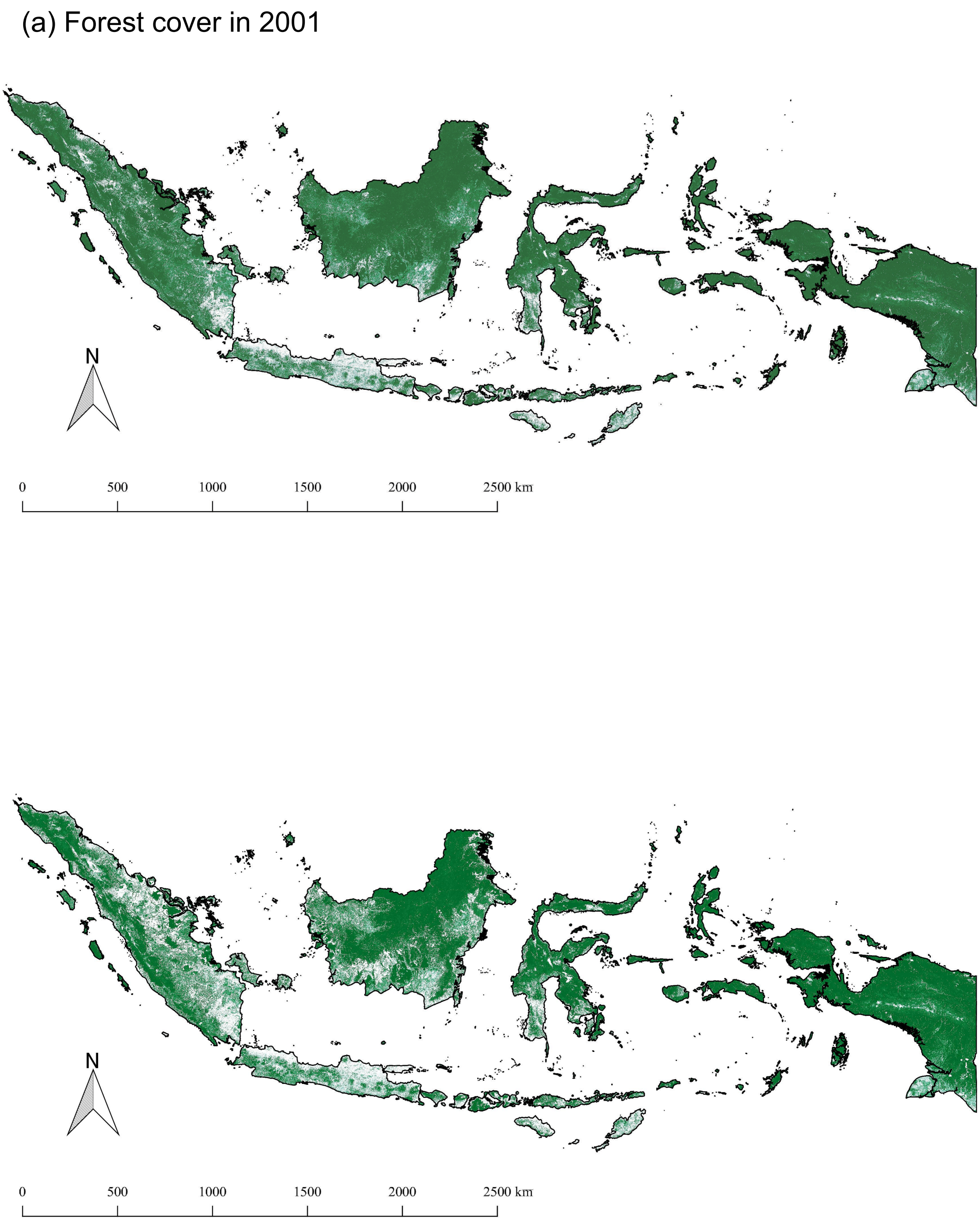


Figure 1: Forest cover change between (a) 2001 and (b) 2014 *source: Hansen et al. (2013).*

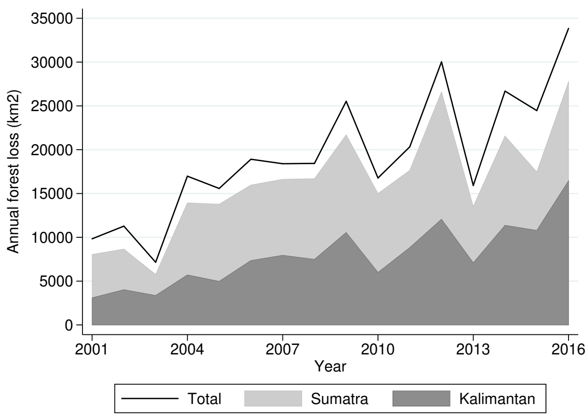


Figure 2: Total annual forest loss for Kalimantan and Sumatra in Indonesia from 2001 to 2016 *source: Hansen et al. (2013).*

Table 1: Descriptive statistics

| | 2000 | 2007 | 2014 |
|---|---|---|---|
| All farmers | | | |
| Log of agricultural production | 14.054 | 14.558 | 14.722 |
| Fcover (Ratio of forest cover in subdistrict) | 0.812 | 0.766 | 0.679 |
| Land size (hectares) | 1.151 | 1.173 | 1.248 |
| Labor input (No. of working-age members) | 2.824 | 3.638 | 4.034 |
| No. of household members | 3.647 | 4.508 | 5.163 |
| Age of household head | 47.016 | 49.400 | 52.366 |
| Schooling years of household head | 5.241 | 5.627 | 6.340 |
| Household head women dummy | 0.098 | 0.112 | 0.125 |
| Family size | 5.890 | 6.800 | 7.674 |
| GDP per capita (billion Indonesian rupiahs) | 4.994 | 6.302 | 7.401 |
| No. of households | 1,281 | 1,296 | 1,150 |
| Rice farmers | 0.504 | 0.500 | 0.413 |
| | | | |
| Farmers produce mainly rice | | | |
| Log of agricultural production | 14.161 | 14.500 | 14.726 |
| Fcover (Ratio of forest cover in subdistrict) | 0.826 | 0.771 | 0.681 |
| Land size (hectares) | 1.116 | 1.010 | 1.054 |
| Labor input (No. of working-age members) | 2.868 | 3.634 | 4.103 |
| No. of household members | 3.721 | 4.528 | 5.356 |
| Age of household head | 47.822 | 49.397 | 53.013 |
| Schooling years of household head | 5.057 | 5.465 | 6.114 |
| Household head women dummy | 0.115 | 0.086 | 0.114 |
| Family size | 6.006 | 6.838 | 7.931 |
| GDP per capita (billion Indonesian rupiahs) | 4.840 | 5.842 | 7.031 |
| No. of households | 646 | 648 | 475 |
| | | | |
| Farmers produce mainly products other than rice | | | |
| Log of agricultural production | 13.945 | 14.615 | 14.720 |
| Fcover (Ratio of forest cover in subdistrict) | 0.798 | 0.760 | 0.677 |
| Land size (hectares) | 1.186 | 1.336 | 1.385 |
| Labor input (No. of working-age members) | 2.778 | 3.642 | 3.985 |
| No. of household members | 3.572 | 4.488 | 5.028 |
| Age of household head | 46.195 | 49.404 | 51.911 |
| Schooling years of household head | 5.428 | 5.789 | 6.499 |
| Household head women dummy | 0.080 | 0.137 | 0.133 |
| Family size | 5.772 | 6.762 | 7.493 |
| GDP per capita (billion Indonesian rupiahs) | 5.150 | 6.762 | 7.661 |
| No. of households | 635 | 648 | 675 |

*Source:* Indonesia Family Life Survey 2000–2014

Table 2: The effects of change in the forest cover rate on agricultural output

| Dependent variable | ln(value of yields per planted area) | | | | |
|---|---|---|---|---|---|
| | | | | | Considering endogeneity of labor input |
| | (1) | (2) | (3) | (4) | (5) |
| Fcover | 3.504(0.912)*** | 3.671(0.772)*** | | 2.241(1.280)* | 3.813(0.782)*** |
| Sumatra & Kalimantan × IFLS5 | | | −0.420(0.094)*** | | |
| ln(land) | | −0.809(0.028)*** | −0.811(0.027)*** | −0.797(0.034)*** | −0.814(0.028)*** |
| ln(labor) | | 0.130(0.072)* | 0.115(0.071) | 0.349(0.166)** | 0.623(0.217)*** |
| ln(asset) | | 0.136(0.016)*** | 0.132(0.016)*** | 0.125(0.022)*** | 0.134(0.017)*** |
| Rice farmer (dummy) | | 0.040(0.072) | 0.069(0.070) | 0.078(0.105) | 0.053(0.073) |
| Age of head | | −0.003(0.004) | −0.003(0.004) | 0.074(0.027)*** | −0.006(0.004) |
| Age of head squared /100 | | 0.000(0.000) | 0.000(0.000) | −0.074(0.025)*** | 0.001(0.000) |
| Schooling years of head | | 0.019(0.014) | 0.020(0.013) | −0.012(0.021) | 0.018(0.014) |
| Head of women dummy | | −0.055(0.103) | −0.049(0.100) | −0.290(0.157)* | −0.009(0.112) |
| GDP per capita | | −0.154(0.054)*** | −0.074(0.057) | −0.209(0.079)*** | −0.157(0.054)*** |
| Constant | 12.033(0.800)*** | 12.244(0.740)*** | 14.789(0.357)*** | 12.276(1.357)*** | 11.833(0.741)*** |
| Year fixed effects | YES | YES | YES | YES | YES |
| Household fixed effects | YES | YES | YES | YES | YES |
| Estimation | OLS | OLS | OLS | 2SLS | 2SLS |
| R-squared | 0.116 | 0.422 | 0.503 | 0.455 | 0.486 |
| Number of observations | 3,259 | 3,259 | 3, 259 | 2, 063 | 3,223 |

Note: (1) The dependent variable in all models is the logarithmic household's agricultural value of yield per planted area.
(2) Numbers in parentheses are standard errors clustered at the household level.
(3) $***$, $**$, and $*$ denote statistical significance at the 1%,5%, and 10% levels, respectively.
(4) The number of samples for column (4) is smaller compared to others because we drop the sample in IFLS 3 due to data limitations.

Table 3: Regression results for various types of output

| Dependent variable | ln(value of yield per planted area) | | | | ln(non-agricultural income) |
|---|---|---|---|---|---|
| | Annual crops | | Perennial crops | | |
| | (1) | (2) | (3) | (4) | (5) |
| Fcover | 2.361(1.238)** | 2.978(0.914)*** | 6.228(3068)** | −2.928(2.582) | 0.331(1.217) |
| Year fixed effects | YES | YES | YES | YES | YES |
| Household fixed effects | YES | YES | YES | YES | YES |
| Sample | Rice farmer | Annual crop farmer | Vulnerable tree farmer | Tolerant tree farmer | Non-farming business |
| R-squared | 0.536 | 0.520 | 0.575 | 0.417 | 0.075 |
| Number of observations | 1,813 | 2,379 | 564 | 458 | 3,369 |

Note: (1) Each column presents the results from separate regressions.
(2) The other covariates for columns (1), (2), (3), and (4) are the same as those in column (2) of Table 2.
(3) The covariates for column (5) are the household characteristics such as age of head, squared age of head, education of head, and household size.
(4) The numbers in parentheses are standard errors clustered at the household level.
(5) *** and ** denote statistical significance at the 1% and 5% levels, respectively.

Table 4: Robustness check

| Dependent variable | ln(value of yields per planted area) | |
|---|---|---|
| | (1) | (2) |
| Fcover | 3.671(0.772)*** | 3.557(0.8727)*** |
| Year fixed effects | YES | YES |
| Household fixed effects | YES | YES |
| Sample | Full sample | Non-drop |
| R-squared | 0.478 | 0.497 |
| Number of observations | 3,259 | 2,182 |

Note: (1) The dependent variable in all models is logarithmic household's value of agricultural yield per planted area.
(2) The other covariates for columns (1), (2), (3), and (4) are the same as those in column (2) of Table 2.
(3) The numbers in parentheses are standard errors clustered at the household level.
(4) $***$ denotes statistical significance at the 1% level.

Table 5: Forest cover and household strategies

| Dependent variable | ln(land size) | | ln(farming asset) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Fcover | 0.156(0.770) | 2.611(1.591) | 0.400(0.840) | 1.707(1.093) |
| Year fixed effects | YES | YES | YES | YES |
| Household fixed effects | YES | YES | YES | YES |
| Sample | Full sample | Rice farmer | Full sample | Rice farmer |
| R-squared | 0.042 | 0.064 | 0.071 | 0.082 |
| Number of observations | 3,259 | 1,813 | 3,259 | 1,813 |

Note: (1) The dependent variables are logarithmic land size for columns (1) and (2); and farming assets that households own for columns (3) and (4).
(2) The numbers in parentheses are standard errors clustered at the household level.
(3) All regressions are estimated using OLS and include household and year fixed effects as well as household characteristics such as age of head, squared age of head, education of head, and household size.

Table 6: Forest and household consumption

| Dependent variable | ln(food consumption) | ln(non food consumption) | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Fcover | 0.331(0.400) | 1.158(0.675)* | 1.756(2.581) | 1.070(2.174) | −1.296(1.606) |
| Year fixed effects | YES | YES | YES | YES | YES |
| Household fixed effects | YES | YES | YES | YES | YES |
| Sample | Full sample | Rice farmer | Perennial crop farmers | Perennial crops + livestock farmers | Non-farming business households |
| R-squared | 0.024 | 0.157 | 0.160 | 0.145 | 0.147 |
| Number of observations | 3,259 | 1,813 | 674 | 797 | 3,369 |

Note: (1) The dependent variable in all models is logarithmic household consumption per capita (IRP).
(2) The numbers in parentheses are standard errors clustered at the household level.
(3) $*$ denotes statistical significance at the 10% level.
(4) All regressions are estimated using OLS and include household and year fixed effects as well as household characteristics such as age of head, squared age of head, education of head, and household size.

Table A1: Regression results with *kecamatan* fixed effects

| Dependent variable | ln(real agricultural output) | |
|---|---|---|
| | (1) | (2) |
| Fcover | 2.247(1.349)$^{*}$ | 3.418(1.272)$^{***}$ |
| ln(land) | | $-0.739(0.028)^{***}$ |
| ln(labor) | | 0.161(0.033)$^{***}$ |
| ln(asset) | | 0.150(0.013)$^{***}$ |
| Rice farmer (dummy) | | 0.130(0.070)$^{*}$ |
| Age of head | | $-0.009(0.002)^{***}$ |
| Age of head squared /100 | | 0.001(0.000)$^{***}$ |
| Schooling years of head | | 0.004(0.006) |
| Head of women dummy | | $-0.287(0.064)^{***}$ |
| GDP per capita | | $-0.150(0.100)$ |
| Constant | 2.247(1.349)$^{*}$ | 13.711(1.238)$^{***}$ |
| Year fixed effects | YES | YES |
| *kecamatan* fixed effects | YES | YES |
| Number of observations | 3,259 | 3,259 |
| R-squared | 0.299 | 0.587 |

Note: (1) The dependent variable in all models is the logarithmic household's value of agricultural yield per planted area.
(2) Numbers in parentheses are standard errors clustered at the household level.
(3) $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Regression results including every type of farmer or Java sample

| Dependent variable | ln(real agricultural output) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Fcover | 2.824(0.976)*** | 3.055(0.700)*** | 0.303(0.645) | −0.254(0.453) |
| ln(land) | | −0.815(0.024)*** | | −0.833(0.015)*** |
| ln(labor) | | 0.065(0.071) | | 0.079(0.051) |
| ln(asset) | | 0.137(0.014)*** | | 0.098(0.011)*** |
| Rice farmer (dummy) | | −0.077(0.063)* | | −0.011(0.056)* |
| Age of head | | −0.001(0.003) | | −0.003(0.003) |
| Age of head squared /100 | | 0.000(0.000) | | 0.000(0.000) |
| Schooling years of head | | 0.020(0.013) | | 0.016(0.010) |
| Head of women dummy | | −0.100(0.096)*** | | −0.170(0.072)** |
| GDP per capita | | −0.190(0.051) | | −0.001(0.045) |
| Constant | 12.189(1.238)*** | 12.804(0.679)*** | 14.730(0.440)*** | 14.630(0.388)*** |
| Year fixed effects | YES | YES | YES | YES |
| Household fixed effects | YES | YES | YES | YES |
| Number of observations | 3,820 | 3,820 | 6,687 | 6,687 |
| R-squared | 0.113 | 0.587 | 0.083 | 0.583 |

Note: (1) The dependent variable in all models is the logarithmic household's value of agricultural yield per planted area.
(2) Numbers in parentheses are standard errors clustered at the household level.
(3) $***$, $**$, and $*$ denote statistical significance at the 1%, 5%, and 10% levels, respectively.
(4) The sample for columns (3) and (4) include households that live in Java island (provinces of Jawa Barat, Jawa Tengah, Jawa Timur, and Yogyakarta).

Table A3: First-stage regressions of columns 4 and 5 in Table 2

| Dependent variable | First stage Fcover | First stage ln(labor) |
|---|---|---|
| | (1) | (2) |
| $\text{Fcover}_{t-1}$ | 0.9382(0.0052)*** | |
| ln(no. of household members) | | 0.439(0.032)*** |
| Year fixed effects | YES | YES |
| Household fixed effects | YES | YES |
| Number of observations | 2,063 | 3,223 |
| R-squared | 0.9985 | 0.387 |
| F-test on the excluded instrument | 46969.92 | 847.12 |

Note: (1) All estimations include household and year fixed effects and household and region controls. See columns 4 and 5 in Table 2 for details on the second stage.
(2) Numbers in parentheses are standard errors clustered at the household level.
(3) $***$ denotes statistical significance at the 1% level.

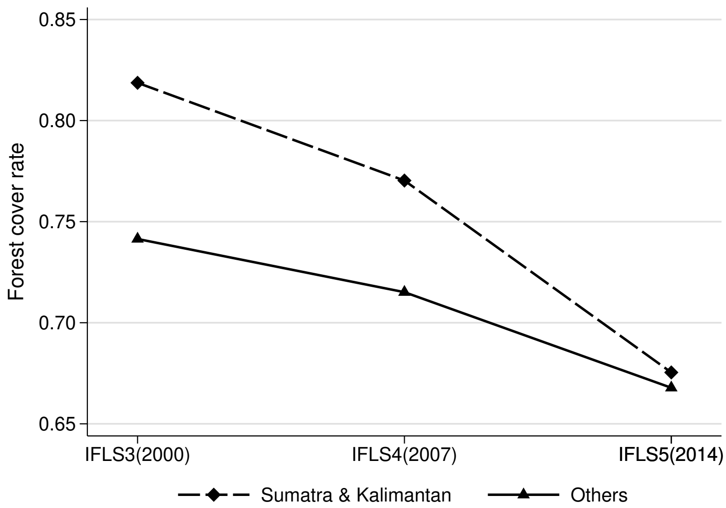


Figure A1: Forest cover change by region

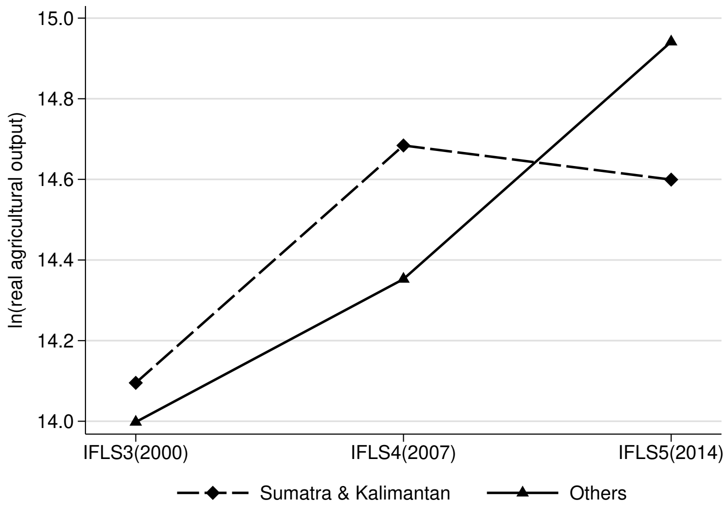


Figure A2: The unconditional mean of ln(real value of agricultural yield per planted area)

Table A4: The classification of crops

<table>
<tr><td colspan="2">Annual crops</td><td>Rice, Cassava, Other tuber, Ground nuts, Soybean, Corn, Red onion, Other vegetables</td></tr>
<tr><td rowspan="2">Perennial crops</td><td>Vulnerable</td><td>Coffee, Banana, Cashew nuts, Coconut, Chili, Other fruits</td></tr>
<tr><td>Tolerant</td><td>Rubber, Wood, Sugarcane, Tobacco, Spice</td></tr>
</table>

*Source:* Indonesia Family Life Survey (IFLS)
Note: (1) the classification for perennial crops is based on strength against pest damage.

Table A5: Descriptive statistics for non-farming business households

| | 2000 | 2007 | 2014 |
|---|---|---|---|
| Households engaging in non-farming business | | | |
| Log of non-farming production | 14.297 | 14.754 | 14.983 |
| Ratio of forest cover in subdistrict | 0.807 | 0.759 | 0.678 |
| Age of household head | 44.828 | 48.101 | 50.250 |
| Schooling years of household head | 6.312 | 7.140 | 7.859 |
| Head of women dummy | 0.141 | 0.139 | 0.163 |
| No. of working-age members | 3.835 | 4.667 | 5.177 |
| No. of children (age<15) | 1.678 | 1.576 | 1.365 |
| GDP per capita | 4.963 | 6.453 | 7.486 |
| Number of observations | 1,092 | 1,191 | 1,089 |

*Source:* Indonesia Family Life Survey 2000–2014