Environmental Consequences of Poverty Alleviation Programs:

Evidence from Conditional Cash Transfer Program in Indonesia

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Abstract:

Although an increasing number of studies measure the effects of environmental programs on poverty, little empirical evidence exists about the effects of poverty programs on the environment. Indonesia, which is home to one of the world's most biologically diverse rainforests, started phasing in a poverty alleviation program in 2007. The program, called the *Program Keluarga Harapan* (PKH), assigns conditional cash transfers to eligible poor households. We seek to estimate the effect of these substantial and persistent income transfers on deforestation. To do so, this study combines administrative data from the PKH and the Indonesian government, remote sensing data from satellites, a deep understanding of how the PKH was scaled up across villages and over time, and econometric methods to control for confounding variables that are correlated with both deforestation and exposure to the PKH. The econometric methods combine semi-parametric matching methods, which control for observable pre-treatment confounding characteristics, with a difference-in-differences (DID) design that uses a fixed-effect, panel data regression estimator to control for unobservable, but time-invariant confounders. Exposure to the PKH decreases annual forest cover loss in a village by an estimated 16.9%, on average. Thus, in Indonesia, efforts to reduce poverty can also yield environmental co-benefits.

I. Introduction

Most carbon and biodiversity-rich tropical rainforests are located in developing countries. These same countries, however, have historically been less focused on protecting their forests and more focused on achieving development objectives, such as poverty reduction and other Millennium Development Goals (MDGs). To achieve their development objectives, governments are increasingly implementing conditional cash transfers (CCT) programs. CCT programs transfer cash or other resources to poor households; funds are conditional on household members accomplishing specific tasks that are believed to promote development (e.g., school attendance, pre- and post-natal health care visits). Over half of the thirty tropical countries with the most forest cover now have CCTs, and others are planning to create them. Despite the widespread growth of CCTs in ecologically rich countries, only one study has examined the impact of CCTs on environmental outcomes (Alix-Garcia, McIntosh, Sims, & Welch, 2013).

Using evidence from the targeted household CCT program in Indonesia (*Program Keluarga Harapan*, PKH), this paper analyzes the effect of a poverty alleviation program on deforestation. The PKH transfers cash to poor households on condition that the households fulfill certain health and education obligations. A conditional cash transfer program can affect deforestation through an increase in household income or through an increase in productivity from the health and education conditions. According to the PKH pilot program evaluation (Alatas, 2011), there is no evidence of changes in long-term health outcomes as well as changes of education behaviors. However, the PKH was effectively increasing average monthly expenditure of beneficiary households by 10%. Based on these findings, this paper focuses on the environmental effect of the program through the increase in income.

Estimating this effect is possible because the temporal and spatial variation in program exposure at the village level is well understood. Geo-referenced, administrative data from the PKH program exist for both pre-PKH and post-PKH years, as well as panel satellite data on changes in forest cover. With a deep understanding of program implementation and a rich data set with which one can apply econometric methods to control for time-varying, observable sources of bias and time-invariant unobservable sources of bias, this paper estimates a program impact that is policy-relevant for Indonesia, i.e., the average treatment effect on the treated, or the average impact on deforestation of PKH exposure at the village level. This study uses econometric methods that combine semi-parametric matching on observable pre-treatment confounding characteristics, followed by panel data estimators that seek to control for unobservable, but time-invariant confounders. Specifically, this paper uses a difference-in-differences (DID) design using a fixed-effect, panel data regression estimator that helps mitigate the confounding effects of time-invariant, village characteristics.

The extent to which CCTs will affect environmental outcomes in tropical countries is unknown. The "poverty-deforestation hypothesis" literature has tried to identify the conditions under which changes in poverty affect deforestation rates, but conclusions vary. For example, in the context of a theoretical model of a small-scale agricultural producer, Angelsen (1999) concludes that when labor markets are imperfect (as they are in tropical countries), deforestation decreases as agriculture productivity or output prices increase. Using a different model of small-scale producers and imperfect labor markets, Zwane (2007) argues that the relationship between an exogenous change in income and land clearing is ambiguous.

Given the ambiguous predictions from theory, empirical tests of the relationship between deforestation and income-transfer programs are critical. Earlier literature attempts to estimate the relationship between income and deforestation across countries using panel designs with random effect and fixed-effect estimators (Cropper & Griffiths, 1994; Koop & Tole, 1999). Given concerns about country-specific unobserved characteristics that might bias the estimators in these designs, more recent studies use within-country analysis rather than cross-country analysis (Alix-Garcia et al., 2013; Foster & Rosenzweig, 2003; Khan & Khan, 2009; Purnamasari, 2010; Zwane, 2007). With two exceptions (Alix-Garcia et al., 2013; Foster & Rosenzweig, 2003), most of these studies do not make strong efforts to eliminate unobserved confounding factors that affect both income and deforestation (violating exclusion restriction for instrumental variable approach). Without such efforts, the estimators might suffer from endogeneity bias.

The two exceptions report conflicting conclusions about the effect of income growth on deforestation. The results in Foster & Rosenzweig (2003) imply that overall income growth (not income growth from a specific program) reduced deforestation in India through its positive impact on demand for forest products. In contrast, the results of Alix-Garcia et al. (2013) imply that the poverty reduction from a Mexican CCT (*Oportunidades*) led to an increase in deforestation. The results from the two studies may differ because their contexts are different: Foster & Rosenzweig focus on India and do not attempt to explain the source of income growth, whereas Alix-Garcia et al. focus on Mexico and focus on income growth that comes from an anti-poverty program. The results may also differ because the study designs differ: Foster & Rosenzweig use an instrumental variable design and Alix-Garcia et al. use a regression discontinuity design. Thus each estimates a subgroup-specific local treatment effect, which may not reflect impacts experienced in the larger population.

In an attempt to measure the environmental impacts of a specific anti-poverty program for a large proportion of the treated rural population, this paper uses Indonesia's PKH. The program began in 2007. To be eligible for the PKH's conditional cash transfers, a household had to fall below 80 percent of the official poverty line, have pregnant women or children, and must comply with specific health and education-related obligations. In 2007, the geographic coverage of the PKH was limited, but coverage has expanded each year since with an aim of eventually covering the entire country. In 2012, all 33 provinces in Indonesia had PKH activity in one or more of their sub-districts. Figure 1 shows the spatial distribution of the PKH.

Although researchers are beginning to evaluate the economic impacts of the PKH program (Alatas, 2011; Nazara & Rahayu, 2013; Triyana, 2013), no one has evaluated its environmental impacts. These environmental impacts, however, are important in a country that is at the center of debates about the relationship between development and the environment. As one of the world's largest tropical rainforests countries, Indonesia is a biodiversity hotspot (Myers, Mittermeier, Mittermeier, da Fonseca, & Kent, 2000). Between 1990 and 2011, Indonesia was also the second largest deforester in the world after Brazil (FAO, 2006). By 2012, the success of Brazil's anti-deforestation program led to Indonesia taking over the number one spot for net primary forest cover loss (Margono, Potapov, Turubanova, Stolle, & Hansen, 2014). Relative to Brazil, Indonesia's deforestation is increasing in both relative terms and absolute terms. Thus understanding the effects of the PKH on environmental outcomes like deforestation is very important.

This study finds that village exposure to the PKH decreased forest cover loss. Compared to untreated villages, villages exposed to the program have lower forest loss: almost 17% lower annually. These results are consistent after performing robustness checks by removing immediate neighbors and removing potentially non-community forest from the data.

The evidence about the PKH's impact sheds light on the broader issue of the environmental effects of CCTs globally and of anti-poverty programs and income changes in general. It also contributes to a more accurate and informative model of regional deforestation models in Asia because it uses variation in village-level data. Kaimowitz and Angelsen (1998) pointed out that most studies in Asia use province-level data. Finally, the evidence from this study also contributes to the sparse literature on the environmental impacts of development programs.

The remainder of the paper is structured as follows. Section II describes the spatial and temporal variations in the Program Keluarga Harapan (PKH) assignment to a sub-district. Section III elaborates how PKH might affect deforestation. Section IV presents the identification strategy to evaluate the impact of the PKH on deforestation followed by results and discussions in section V. Section VI concludes the results and highlights the implication of the results.

II. The Program Keluarga Harapan (PKH)

In 2007, the Government of Indonesia (GOI) implemented a targeted household conditional cash transfers (CCTs) program called the *Program Keluarga Harapan* (PKH, or the Hopeful Family Program). The PKH transfers cash to mothers in poor households on a quarterly basis. The amount of the transfer varies between Rp 600,000 to Rp 2,200,000 annually based on their eligibility conditions. These amounts are approximately equal to 15 to 20 percent of the estimated consumption of poor households (Sparrow, 2008). To be eligible to receive the PKH transfers, a household must be categorized as extremely poor households and must have either one or more of these following conditions: i) pregnant or lactating mothers, ii) child aged less than 6 years, iii) children of primary school age, iv) children of secondary school age.

Similar to other conditional cash transfers programs such as Brazil's *Bolsa Familia* and Mexico's *Oportunidades*, the PKH aims to improve extreme poor households' welfare and break intergenerational poverty by providing cash transfers with health and education obligations attached to them. These health conditions include pre-natal check-ups, iron tablet consumption and birth assistance by a trained professional for pregnant mothers. Lactating mothers have to complete post-natal care visits. Households with children aged 0-6 years must complete childhood immunizations, take vitamin A and fulfill growth-monitoring check-ups. For education obligations, households with children aged 6-15 years must enroll their children at either primary school or junior secondary school with a minimum attendance of 85% of school days. Finally, households with children aged 16-18 years who have not completed nine years of primary and secondary school must enroll their children in an education program to complete 9 years education equivalent to receive the PKH transfers.

The PKH is a large scale social assistance program in Indonesia that involves a coordination of several ministries and government agencies including the Ministry of Social Affairs (Kemensos), the Coordinating Ministry for Social Welfare (Kemenkokesra), the Ministry of National Education (Kemdiknas), the Ministry of Health (Kemenkes), the Ministry of Communication and Information (Kemenkominfo), Statistics Indonesia (BPS), the State Ministry of National Development Planning (Bappenas) and the national post office (PT. Pos). Combined with two other social assistance programs, the plan of the program will cover a third of the Indonesian population. This makes it the largest social assistance program in the world ("Full of promise | The Economist," 2015). With this large expansion plan, the PKH was designed with a rigorous monitoring and evaluation method from the beginning. In the pilot phase of the program implemented in 2007, seven provinces were selected with random assignment of the PKH at the sub-district level. These seven provinces were West and East Java, DKI Jakarta, East Nusa Tenggara, North Sulawesi, Gorontalo and West Sumatera[1].

Two years after the implementation of the 2007 PKH pilot phase, Alatas (2011) evaluates the effect of the PKH on beneficiary households' income, health and education outcomes. The PKH successfully improved beneficiary households' average monthly expenditure and the usage of primary healthcare services. However, there is no evidence of the PKH effects on long-term health and education outcomes.

This paper exploits the PKH geographical targeting as an identification strategy to analyze the environmental effects of the PKH. The GOI assigns the PKH to a sub-district level of administrative division. The PKH assignment from the central government to a sub-district was based on several criteria. From the central government, the PKH was assigned to a province was based on geographical representations including high/medium/low poverty rate, urban/rural areas, coastal-areas/islands and level of difficulties to access the areas (Sparrow, 2008). Within a province, districts were selected based on development considerations including high incidence of poverty, health and education outcomes and facilities and approval from the local government to accept the implementation of the PKH. Since the PKH has health and education obligations attached to the cash transfers, sub-districts' ability to accommodate the potential increasing demand of health and education services, i.e. sub-districts' supply-side readiness, was an important aspect for the PKH assignment. The GOI assessed existing health and education facilities and providers in each sub-districts to determine their supply-side readiness. Sub-districts that were considered supply-side ready were then randomly selected to a treatment and a control group in the pilot program in 2007.

[1] Unlike the rest of the six provinces, West Sumatera was included in the pilot program due to the head of district's

Starting in 2008, the PKH was expanded to cover more provinces in Indonesia. Documentation on the PKH assignment criteria in the scale-up program (2008-onward) was very limited. It is not clear whether the GOI still applies the same assignment criteria as in the pilot program. To overcome this lack of documentation, this study conducted a field survey from July to September 2016. We interviewed the PKH program administrators, agencies and heads of the villages in 32 rural villages from 5 provinces other than Java. Based on these interviews, the PKH was assigned to a sub-district using the same assignment criteria as in the pilot program in 2007. However, the PKH assignment to supply-side ready sub-districts was no longer random from 2008 onward.

All districts that were offered the PKH in the research area of interest accepted the PKH[2]. In the scale-up phase, the number of the PKH eligible households plays an important role in determining the assignment of the PKH to a sub-district. Among the supply-side ready sub-districts, sub-district with a high number of the PKH eligible households will be prioritized to receive the PKH earlier than others. This issue might exist due to the pressure to expand the PKH to cover all of the provinces in Indonesia and the PKH's budget constraint.

The number of the PKH eligible households is provided independently by Statistics Indonesia. To obtain data on poor households, Statistics Indonesia surveyed poor and extremely poor households that were drawn from the list of beneficiaries of the 2005 unconditional cash transfers program known as PSE05. Due to the imprecise list of poor households in PSE05, Statistics Indonesia removed 30 to 40% households from the list and added about 5% of newly poor households from interviewing poor households in the PKH targeted sub-districts (Alatas, 2011). From the list of extremely poor households, Statistics Indonesia identified eligible

[2] Some districts in Java refused the PKH. Since this paper uses forest area in Indonesia, Java was excluded from the sample.

household that met PKH program criteria of pregnant or lactating women, children age 0-15 years, and children age 16-18 years who have not yet completed 9 years of basic education.

The PKH implementing agency, The Kemensos was responsible for the final approval of the beneficiary list. The PKH implementation Unit (UPPKH), a division of the Kemensos approved the final beneficiary list that included very poor and a small percentage of poor households (Alatas, 2011). The Kemensos then disseminates the list of the PKH-eligible households directly to the PKH facilitators in a selected sub-district. Since the list was obtained in 2005 and the PKH was implemented starting from 2007, some of the eligible households in the initial list were no longer qualified for the PKH. The PKH facilitators verified whether the eligible households are categorized as poor, based on their physical assets, or whether they still have the PKH components.

The PKH facilitators can remove households from the list but they cannot add new poor eligible households to the list even after the strong recommendation from the village officials. Statistics Indonesia, through a survey that is conducted every 3 years, is the only agency that can produce the list. The rigid targeting of the PKH to households gives advantage to the identification strategy. For example, if the village itself demanded to get the program rather than following the known assignment program.

Figure 2 summarizes the flow of the PKH assignment from a province to a village level of administration. Within a province, districts were offered the PKH based on their poverty incidence and no districts in the sampling area of this paper rejected the offer. Sub-districts that are categorized as supply-side ready based on their access to health and education facilities received the PKH based on their number of the PKH eligible households. Villages within the selected sub-district will receive the PKH based on the number of eligible households in the village.

III. The PKH and Forest Cover Loss

The direction in which a conditional cash transfer program such as the PKH will affect deforestation is ambiguous. An increase in income from the PKH can either exacerbate or reduce deforestation. The PKH can directly affect the poor households decisions regarding consumption smoothing and land investment.

Consumption smoothing has been one of the deforestation motives by low-income households in developing countries. With limited credit access, poor households diversify their activities to smooth income fluctuations. Most of the poor households in developing countries work in the agricultural sector. To smooth the seasonal income from the agricultural sector, poor households depend on forest products to generate additional income. Several studies show empirical analysis on the use of forest products as a coping mechanism to mitigate income shocks for low-income households in the Brazilian Amazon (Pattanayak & Sills, 2001), in Peru (Takasaki, Barham, & Coomes, 2004) and in Malawi (M. Fisher & Shively, 2005). The regular cash transfers provided by the PKH could potentially make households move away from the utilization of forest products as a consumption smoothing mechanism.

This consumption smoothing using forest products is partly due to the nature of forest in Indonesia. From Indonesian law, the Government of Indonesia owns the forest. However, in practice, forests are often perceived as open-access by local communities (Purnamasari, 2010). Local communities are able to deforest at a small-scale because of imperfect property rights and because local and regional governments find it difficult, financially and politically, to monitor and enforce forest laws.

The PKH can also relax the liquidity constraint for poor people to invest on land holding. Bazzi (forthcoming) identifies that rural areas in Indonesia suffer from a liquidity constraint. Although the PKH was not specifically designed to target productive activity or land investment, the cash distributed to the poor households is fungible. The PKH facilitator encourages the households to spend the money on education and health expenditures, but the households determined the final spending of the money. The evaluation of the PKH pilot program suggests that the PKH increases average monthly expenditure for the beneficiary households by 10% compared to pre-program levels (Alatas, 2011). The effects of the PKH on forest cover might be mediated through the increase of land holding for agricultural production in which most rural Indonesian households engage. As income rises, credit-constrained farmers can accumulate more capital, which allows them to engage in more clear cutting of the forest for small-scale agricultural production (Purnamasari, 2010).

The PKH might also affect forest cover loss indirectly. The evidence shows that the PKH beneficiary households spend their additional income for food, especially high protein food and health costs. The increased demand for agricultural products is likely to have a negative effect on forest cover. The results in (Alix-Garcia et al., 2013) show that Mexico's conditional cash transfer program increases the demand for agricultural products. To meet the increasing demand of agricultural products, forest area was converted to agricultural land.

Another indirect effect of the PKH might be mediated trough an increase in the demand for forest products. An increase in the demand for forest products may increase or decrease forest cover, depending on the production function that supplies the products and the property rights regimes that govern forest management investments. For example, Foster & Rosenzweig (2003) argued that income increases fueled demand increases for fuel wood, which led to a shift in land use toward forests.

IV. Identification Strategy

This study estimates the Average Treatment Effect on the Treated (ATT) of the PKH on forest cover loss in Indonesia. The ATT represents the effect of the PKH on forest cover change in those areas that were exposed to the PKH. Formally, the outcome of interest is denoted as Y, while the treatment is denoted as D. Treatment takes on two values: D=1 indicates PKH assignment while D=0 indicates PKH non-assignment. The estimand of interest is Average Treatment Effect on the Treated (ATT).

$$ATT = E[Y_1 - Y_0 | D = 1] \ldots (1)$$

$[Y_1 | D = 1]$ = the observed outcome of the treated unit in the presence of the intervention

$[Y_0 | D = 1]$ = the counterfactual outcome of the treated unit in the absence of the intervention

However, one can never observe the counterfactual outcome of the treated unit in the absence of the intervention. Randomized allocation of the treatment to some units ensures that the expected outcome of the untreated group is equal to the expected counterfactual outcome for the treated group. In other words, if the assignment of the PKH to villages were random, a simple difference-in-differences estimator of the mean outcomes between PKH and non-PKH villages is an unbiased estimator of the ATT.

In the forested areas of Indonesia, however, the assignment of the PKH was not random. With non-random assignment, the expected changes in villages' forest cover loss in PKH and non-PKH villages are likely to be different in the absence of the PKH. To obtain appropriate counterfactuals for the treated villages, this paper controls for different baseline characteristics that affect both the PKH assignment and changes in forest cover loss. These characteristics are chosen based on the PKH selection criteria to villages and historical forest cover loss.

To address this concern about bias from non-random treatment assignment, we pre-processed the data using a matching algorithm that strives to make the treated and untreated villages similar on key observable characteristics known to affect both assignment to the PKH and forest cover change (Ho, Imai, King, & Stuart, 2007).

Pre-processing using matching adjusts the data for potential confounding factors semi-parametrically. The adjustment of the data requires the inclusion of observable characteristics, *X*, that affect the selection of area into the PKH recipients and forest cover change in the matching process. The associated estimand becomes:

$$ATT = E[Y_1 - Y_0|X, D = 1] \ldots (2)$$

The treated group consists of villages that received the PKH from 2008 to 2012. We construct a counterfactual group for the PKH treated villages from villages that did not receive the PKH by 2012 within the same province. Villages did not self-select into the PKH recipient group. Villages that are located in a supply-ready sub-district with a high number of the PKH eligible households received the program.

Equation (2) means that once we conditioned on X, the treatment assignment is “as if” randomly assigned. Hence, the expected outcome of the untreated group, the group that did not receive the treatment, is a valid counterfactual of expected outcome for the treated group; i.e., $E[Y_0|X, D = 1] = E[Y_0|X, D = 0]$, a conditional mean independence assumption. Thus the conditioning set *X* comprises observable the PKH assignment indicators and variables affecting both poverty and forest outcomes including pre-treatment forest losses and forest cover. Pre-treatment outcomes would also be included in the observed conditioning set to block a variety of back-door paths via unobservable variables that affect forest cover in both the past and the future.

To match treated and untreated villages, this paper uses pre-treatment forest loss. Pre-treatment forest loss used in this paper goes back to 2 years before the treatment period. Moreover, this study matches on the forest cover at the beginning of the treatment year. This covariate serves as a normalization of the extent of the forest cover loss across villages. The selection variable used to control the assignment of the PKH to a village is the number of the PKH eligible households. As mentioned in section II, this variable has an important role in determining the selection at the sub-district level. Another covariate used for the pre-processing using matching is length of roads in 2010. Table 3 summarizes the core matching covariates used in this paper.

In addition to the core matching covariates, we also perform matching on the extended covariates. The extended covariates include the core covariates and 2 additional selection covariates, namely access to health and education facilities. From the discussion in section II, the number of the PKH eligible households is the main criteria for the PKH assignment. However, sub-districts' supply-side readiness criteria might also determine the PKH assignment. Hence, we will include these criteria for robustness check. Table 4 describes the extended matching covariates used in the analysis.

In order to consistently estimate the ATT, several other assumptions need to be maintained: (i) Stable Unit Treatment Value Assumption (SUTVA) or no interference among units assumption, i.e.: the value of the treated outcome that will be the same regardless of the assignment mechanism used and regardless of treatments received by other units; and (ii)

Common support with P(D=1|X)<1 to rule out the perfect predictability of treatment assignment, D, after conditioning for X.

The conditional mean independence assumption is plausible because of the assignment procedure was known: a PKH-eligible village had to be in a sub-district with high PKH-eligible households with supply-side ready characteristics. To provide indirect support for the conditional mean independence assumption, this study will show the covariates balance between treated and untreated groups before and after matching. SUTVA or no interference among units assumption is plausible after performing fixed effect regression. In this case, interference among unit is assumed to be constant over time. As a robustness check for the SUTVA assumption, this paper removes the untreated villages that shared boundaries with treated villages and perform matching with the new untreated group.

The common support assumption is most likely to be satisfied because not all of the villages in the supply ready sub-districts are treated in 2012, the end of our observation period. Villages in the supply-side ready sub-districts might not be treated due to the pressure of expanding the program to cover more provinces and budget constraint. Hence, after matching on supply-side readiness criterion and number of extremely poor households, the PKH treatment assignment is as if randomly assigned.

Propensity score estimate is consistent only if matching on the associated propensity score asymptotically balances the observed covariates (Ho et al., 2007). To achieve covariates balance, Rosenbaum & Rubin (1984) recommend iteratively checking if matching on the estimated propensity score produces balance by revising the specification of the propensity score until covariate imbalance is minimized. Since matching does not use outcome data in the post-treatment period, the practice of iteratively checking and revising the specification to minimized covariate imbalance is permissible (Rubin, 2008).

Genetic Matching (Diamond & Sekhon, 2012) is a matching algorithm that eliminates the need to manually and iteratively checks the propensity score (Diamond and Sekhon, 2012). It is a generalization of propensity score and Mahalanobis distance (MD) matching algorithm. Genetic Matching automates the iterative process of checking and improving overall covariate balance and guarantees asymptotic convergence to the optimal matched sample. It may or may not decrease the bias in the conditional estimates. It is recommended that the loss function include individual balance measures that are sensitive to many forms of imbalance such as Kolmogorov-Smirnov (KS) test statistics. This paper is going to consider 2 test statistics to test for covariates balance, namely: t-test and KS-test. Effective matching will produce non-statistical difference between treated and untreated groups after matching.

Matching is unlikely to remove all of the bias in our estimator, both because of imperfect matching in finite samples and because of unobservable confounding factors. Following the suggestion of (Ho et al., 2007), we impose parametric procedures on the pre-processed data set. Specifically, this study uses a fixed effect panel design to mitigate the confounding effects of unobservable, time-invariant characteristics. Suppose there exists forest cover loss spillover among sub-districts, fixed effect panel regression design helps remove the constant spillover. As fixed effect panel regression design assumes homogenous treatment effects, the treated and untreated units respond similarly, on average, to common shocks. To the extent that treatment effect heterogeneity and responses to common shocks are a function of observable characteristics and time-invariant unobservable characteristics, the combined designs of pre-processing using matching and fixed effect panel regression will make these assumptions more plausible (Ferraro & Miranda, 2014).

To estimate the effect of a poverty alleviation program on forest cover, this paper uses difference-in-differences (DID) method using fixed effect panel regression design. Using treated and matched untreated units; ATT is estimated by the difference on forest cover outcome between these two groups.

$$Y_{it} = \beta_0 + \beta_1 PKH_{it} + \beta_2 X_{it} + \alpha_i + \gamma_t + \epsilon_{it} \quad \ldots (3)$$

The unit of analysis in this paper is the village level of administration. Y_{it} is the forest cover loss in village i at year t from panel data, 2001 to 2014. Our coefficient of interest is β_1, which indicates the effect of exposure to the PKH program on Y_{it}. X_{it} consists of time variant characteristics that might affect forest cover loss including average temperature and precipitation rate. The fixed effect, α_i, captures unit's unobserved time invariant characteristics that affect forest cover loss. Time variable, γ_t, represents macro time-varying characteristics that affect forest cover loss. Random error term is represented by ϵ_{it}. Table 5 summarizes the variables used to perform the fixed effect regression analysis.

The PKH was assigned to sub-district level of administrative that comprises several villages. Meanwhile, our unit of analysis is at the village level of administrative. To control for intra-class correlation, this paper is clustering the observations at the sub-district level.

Data

The outcome variable of deforestation is forest cover loss from Hansen et al. (2013). Forest cover loss is defined as a stand-replacement disturbance or the complete removal of tree cover. Tree cover is indicated by a Landsat pixel covered by all vegetation higher than 5 meters in the beginning of a year (January) with a 75% threshold of canopy cover. Hansen et al. (2013) use a high-resolution satellite, Landsat 7, at a spatial resolution of 30 meters to measure forest cover change from 2000 to 2012 globally. This dataset provides a uniform and consistent measure of forest cover and forest loss for all global land at an impressive small spatial resolution. To obtain a dataset on forest cover change for each village in Indonesia, this paper overlaps the Hansen data set with the 2013 Indonesia's village boundaries. While most available polygon data on Asia's developing countries are available only to the provincial level, this village boundaries data gives one of the best and most updated information on the smallest level of administrative in developing countries.

Combining these two datasets gives a small room for forest cover interpolation around the village's boundaries. Since the spatial resolution of the Hansen dataset is small enough, we can measure in details the variation of forest cover across villages. The Indonesia's village boundary in 2013 also serves the purpose to track the villages that received PKH more accurately.

Since the implementation of a regional autonomy law in Indonesia in 2000 (Brodjonegoro & Martinez-Vazquez, 2004), Indonesia experienced a proliferation of administrative areas. The proliferation of administrative areas ranges from the establishment of new villages to a new district that separates itself from the old one. The concern over this proliferation is that we will not be able to identify which village received the PKH because of the changing in the name of the village or the village's code. The list of villages that received the PKH from 2007 to 2012 was obtained from the State Ministry of National Development Planning (BAPPENAS). This treated village dataset gives a village identification using the name and the official village code from Statistic Indonesia in 2014. If we were using the village boundaries in the earlier year, for example the 2007 village boundaries (the earliest edition of this data), then we might not be able to match the treated village with the village boundaries dataset.

Understanding the assignment of the PKH, this paper uses three variables to indicate the selection of a sub-district. As mentioned in section II, the most important variable is the number of eligible households within a sub-district. This variable is used as a matching covariate to produce untreated group that is similar to the treated group. The other variables are access to health and education facilities within a sub-district. These variables were obtained from the World Bank Indonesia office. Although not directly implementing the PKH, The World Bank is the agency evaluating the PKH pilot program.

Government of Indonesia does not target the village as a unit of the PKH assignment. All villages within a selected sub-district are supposed to receive the PKH. However, from the data, there are several instances where not all villages within a sub-district receive the PKH. This issue might be contributed from 3 factors: i) there are no listed eligible households within the village, ii) there is a missing factor, or iii) random error. Using the qualitative observation from the field survey, 20% of the pre-chosen untreated villages within the same sub-district that has treated villages cannot be visited due to transportation access. To control for a confounding factor in the PKH assignment and the forest cover loss, this paper includes length of roads in 2010 as a measure of transportation access in a village.

To control for weather anomalies that might affect forest cover loss, this paper uses yearly average precipitation rate and average surface temperature from NASA. Furthermore, slope has been used as a factor that represents land’s accessibility to be deforested. Low terrain that is suitable for agriculture has higher pressure to be converted while steep terrain land mostly untouched. To control for this potential confounding factor, this paper shows the covariate balance on slope for treated and untreated groups after matching.

One of the caveats from Hansen dataset comes from the definition of the tree cover. Palm oil and rubber plantations might be categorized as forest in this dataset (Tropek et al., 2014). Mature plantations often are replaced by a complete removal of the palm oil and rubber trees from the plot of land. To remove this activity from our forest cover loss definition, this paper will remove plots of land that have legal concessions over them. These concessions datasets were obtained from Indonesia Ministry of Forestry using access through the Global Forest Watch.

Tree cover loss defined by Hansen (2013) may occur for many reasons including deforestation, fire and logging within the sustainable forestry operations area. To get more specific value for deforestation, this study eliminates other causes of tree cover loss by removing wood fiber concessions and logging concessions. This study also removes protected areas from each village area. Removal of the protected areas was done to distinguish the forest area that is managed by the government from the community forest.

This study overlaps the Hansen's data with the Indonesia's 2013 village boundary using gfcanalysis package in R (Zvoleff, n.d.). The spatial mapping of the treated villages was created using geographical information software ArcGIS 10.3. The resulting data set consists of a panel of treated and untreated villages' forest cover and forest cover loss that expands from 2001 to 2012. Tabe 1 summarizes the variables and the sources of the variables used in this paper.

The geographical sample used in this paper includes villages in Sumatera, Kalimantan, Bali and West Nusa Tenggara. All villages in these areas received the PKH starting from 2008, except the villages in one district in West Sumatera. These particular villages in West Sumatera have been removed from the sample due to the issue of a different assignment process explained in section II. Hence, the treatment period of the overall sample starts in 2008. In this paper, treated village is defined as a village that received the PKH between 2008 and 2012. Untreated villages are the villages that did not receive the PKH by 2012.

V. Preliminary Results

Pre-processing data using Matching

As expected from the matching theory, Genetic Matching (GenMatch) minimizes the covariate imbalance. Comparing the p-values from KS and t-test statistics, GenMatch provides better covariate balance compared to propensity score matching[3]. Because covariate balance serves as an indirect test that the treatment assignment was as if randomly assigned between treated and untreated villages, matched observations from GenMatch are used as inputs for the fixed-effects regression.

Based on the PKH program assignment, matching was performed within each of the 16 provinces in Indonesia listed in table 2. Covariates balance is measured using: i) the absolute mean differences between treated and untreated groups, ii) the p-value of t-statistics, iii) the p-value of Kolmogorov-Smirnov (KS) statistics or iv) percentage of dropped observations from caliper matching. Using the first criteria, matching was considered successful if the mean differences between treated and untreated groups post-matching are smaller compared to the mean differences prior matching. P-value from t-statistics provides more informative analysis of whether the covariates means of the treated group are statistically different than the means of the untreated group. The third criterion provides the most stringent decision as it tests whether the covariates in untreated group have the same distributions as the covariates in treated group.

[3] Results are available upon request

Eight of 16 provinces obtain covariates balance as measured by the explained criteria. The last column of table 2 provides information of which provinces achieve the covariates balance. To obtain the most conservative estimate, I applied only the third and fourth criteria to measure covariates balance. As a result, there are 5 provinces that achieve covariates balance measured by non-statistical KS p-values on all matching covariates and retain more than 50% observation after caliper matching with 0.25 standard deviation. Figure 3 summarizes the covariates balance criteria used in this paper.

Figure 4 shows the forest cover loss trends between treated and untreated groups for the complete 16 provinces. Compared to unmatched untreated group, the treated group has lower forest cover loss prior to the first PKH implementation in 2008. After matching, the forest cover loss trend for untreated group tracks closely with the trend in the treated group.

Table 6 shows the covariates balance for the core covariates that might affect the PKH assignment and post-treatment forest cover loss. Treated villages experienced lower forest loss and forest cover compared to the untreated villages. In terms of transportation access, the treated villages have lower length of roads within the village compared to the untreated villages. These same treated villages also have a high number of households that are eligible for the PKH. In general, treated villages are poorer with less access and lower forest loss compared to the untreated villages.

Matching allows us to obtain untreated villages that are more similar in characteristics to the treated villages. From table 6, the mean differences of all core covariates between treated and untreated groups are smaller after matching. Before matching, the p-values for t-statistics indicate a statistical difference between the treated and untreated groups. After matching, the p-values indicate no statistical differences at 95% of confidence interval. Forest cover loss trends prior to the treatment and covariates balances for 8 and 5 balanced provinces are available in the appendices.

Table 7 shows the covariates balance for the extended set of covariates. Overall, the mean differences are smaller after matching and the p-values are statistically not significant. After matching, the treated group is not statistically different than the untreated groups in terms of these covariates that are known to affect the assignment of PKH or forest cover loss.

Fixed Effect Regressions

Table 8 summarizes the results for fixed effect regressions of equation (3) with standard error clustered at sub-district level. The left panel of table 8 provides the results of fixed effect regression without pre-processing using matching. Villages' exposure to the PKH decreases forest loss by 20.33 hectares. The right panel of table 8 shows the results of the fixed effect regression after pre-processing the data by matching on core covariates. Villages that received the PKH decreases forest loss by 2.749 hectares compared to untreated villages. The average annual forest loss in the untreated villages from 2008 to 2012 is 16.29 hectares. Hence, the effect of the PKH corresponds to a decrease of forest loss by 16.9% annually compared to the untreated villages.

The decrease in forest loss is consistent even after adding more covariates on the matching procedure. Table 9 shows the fixed effect regression results after pre-processing using matching on the extended covariates. A village exposure to the PKH decreases forest loss by 2.917 hectares. This number corresponds to 18.13% decrease of forest loss compared to the untreated villages.

The results from the complete 16, 8 and 5 provinces are consistent with the results from the fixed effect regression results[4]. An exposure to the PKH decreases forest loss. However, the point estimates from the specification without matching are bigger compared to the fixed effect using the matched samples. These results are not surprising since the mean forest loss of the untreated group is higher compared to the treated group even prior to the PKH. Generally, pre-processing using matching improves the precision of the point estimate as their confidence intervals become narrower.

To test for no-interference assumption, this paper removes the untreated villages that share administrative boundaries with the treated villages. If there were a spillover or displacement of forest loss from treated villages to their immediate neighbors, then our estimates are bias upward. Table 10 summarizes the results of the fixed effect regressions after removing the immediate neighbors. It shows that the results do not change significantly. Treated villages experienced decrease in forest loss by 3.058 hectares compared to untreated villages.

Addressing the concern regarding a non-forest classification over the definition of tree cover on Hansen (2013) data, this paper performed a robustness check by removing plots of land that were registered as palm oil concessions. Furthermore, to distinguish a legal production forest from the community forest, this paper removes plots of land that were registered as wood fiber and logging concessions. Finally, this paper also removes plots of land categorized as protected areas in 2010. Although community often perceived forest as open access in many parts of Indonesia (Purnamasari, 2010), legally households cannot deforest within the protected areas. Qualitative field interviews with head of the villages in Indonesia indicate that households who reside in plots of land that later on categorized as protected areas can not get land certification.

[4] Table A5 and A6 in the appendices show the fixed effect regression results for the complete 16, 8 and 5 provinces.

The removal of these types of land serves to produce the most conservative estimate of the effect of the PKH.

Table 11 shows the results of fixed effect regression results after removing concessions and protected areas. The right panel shows the effect using the matched samples. A village exposure to PKH consistently decreases forest cover loss even after the removal of concessions and protected areas. These point estimates are smaller compared to the earlier estimates without the removal indicating that households might deforest in the protected or concession areas rather than in community or private forests.

Finally, table 12 summarizes the impact of PKH on forest loss from all of the specifications used in this paper. There is a consistent decrease on forest loss through different specifications. Point estimates from matching specifications are lower compared to without matching specifications.

VI. Conclusion

Due to a high spatial overlap between poverty and biodiversity regions (B. Fisher & Christopher, 2007), understanding the effect of poverty reduction to environmental outcomes becomes crucial. How poverty alleviation programs might affect environmental outcomes has been difficult to answer due to the endogeneity between poverty and forest cover. This paper focuses on the environmental effect of poverty alleviation programs through increase in income. In a developing country like Indonesia, most of poor people in rural areas work in agricultural sector. Income in agricultural sector is known to be seasonal and tend to fluctuate. Poor people who have limited access to credit often use forest products to cope with income fluctuations from agricultural sector. The regular cash transfers from the PKH might decrease the pressure on forest.

Using the PKH geographical targeting as the identification strategy, this paper finds that village exposure to the PKH decreases forest cover loss by 17% to 18% compared to untreated villages. These results are significant over different samples and specifications. These results are also robust after considering the spatial spillovers in the analysis. Thus, this paper finds no evidence that increases in income increases forest cover loss.

In contrast, Alix-Garcia et al (2013) estimated that conditional cash transfers in Mexico increased deforestation. Their opposite conclusion could arise from different contexts (Mexico vs. Indonesia) or from different study designs. The estimand for this Indonesia study is the average treatment effect on the treated villages. The estimand for the Mexico study is a local average treatment effect around an eligibility threshold based on a poverty index, i.e., it measures the treatment effect for only communities just above or just below the eligibility threshold.

This paper shows that in the context of Indonesia, effort to reduce poverty is followed by environmental benefits. The treatment effect estimated in this paper is policy relevant as it uses a large and heterogeneous sample from all the administrative units that have received the PKH. Deforestation in Indonesia is not only a problem of losing a forest cover but also a problem of how it losses its forest cover. Indonesia losses its forest mostly by slash and burn practice. In 2015, Indonesia has rampant forest fires that significantly affect both the environment and people's health (Balch, 2015). As Indonesia currently has no carefully designed environmental policies, the income from the PKH helps reducing the pressure to do slash and burn on forest area. The PKH contributes to cost saving from preventing forest fires and costs from fire-induced health problems and environmental degradation.

This study contributes to the sparse literature on the environmental impacts of development programs. It also contributes to a more accurate and informative model of regional deforestation models in Asia because it uses variation in village-level data. This study also finds that a CCT program can have a wide range of impacts that go beyond the program objectives.

One weakness of this study is its reduced form approach to estimating the effect of the PKH on forest cover loss. Although the linkages elaborated in section III provide potential explanations of what causes the causal effect between the PKH to forest cover loss, the exact mechanisms through which PKH reduced deforestation are unknown. Identifying these mechanisms, and their relative contributions to the overall impact, will be a future direction of research from this paper.

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1 Tables

Table 1: Data

Variable	Source
Forest loss & forest cover 2001-2012	Hansen et.al. (2013) version 1.2
Village boundaries 2013	Statistics Indonesia
PKH villages	The State Ministry of National Development Planning (BAPPENAS)
Number of poor people in a district	Statistics Indonesia
Number of eligible households in a sub-district	the World Bank (Indonesia Office)
Access to health facilities in a sub-district	the World Bank (Indonesia Office)
Access to education facilities in a sub-district	the World Bank (Indonesia Office)
Road length in 2010	Socioeconomic Data and Applications Center (SEDAC)
Precipitation rate	TRMM 3B43 V.7
Yearly average surface temperature	M2TMNXFLX V5.12.4
Slope	SRTM 90m Digital Elevation Database v.4.1
Palm oil concessions	Indonesia Ministry of Forestry accessed through Global Forest Watch
Wood fiber concessions	Indonesia Ministry of Forestry accessed through Global Forest Watch
Logging concessions	Indonesia Ministry of Forestry accessed through Global Forest Watch
Protected areas 2010	World Database of Protected Areas

Table 2: Provinces

No	Province Number	Province Name	Number of Treated Villages	Number of Untreated Villages	First PKH Year	Covariates Balance
1	11	Nanggroe Aceh Darussalam	2,581	3,664	2008	
2	12	North Sumatera	872	4,929	2008	
3	13	West Sumatera	83	799	2010*	Balance**
4	14	Riau	331	1,144	2011	Balance**
5	15	Jambi	47	1,179	2012	
6	16	South Sumatera	674	2,207	2009	
7	17	Bengkulu	275	1,008	2010	
8	18	Lampung	1,120	1,080	2009	
9	19	Kepulauan Bangka Belitung	51	273	2012	
10	21	Kepulauan Riau	115	156	2008	Balance
11	51	Bali	213	492	2010	Balance**
12	52	West Nusa Tenggara	677	197	2008	
13	61	West Kalimantan	232	1,373	2010	Balance**
14	62	Central Kalimantan	123	1,196	2008	Balance
15	63	South Kalimantan	598	1,359	2008	Balance
16	64	East Kalimantan	116	832	2011	Balance**

*Started at 2007 for pilot project but contaminated due to district's pressure to be included in the program
**Balanced on p-value KS

Table 3: Matching Covariates: Core Covariates

Variable Categories	Variable Name	Description	Unit
Outcome	$forestloss_{i,t+1}$	forest cover loss in village i one year post-PKH	hectare
Pre-Treatment Outcomes	$forestloss_{i,t-2}$	forest cover loss in village i 2 years prior to the PKH	hectare
	$forestloss_{i,t-1}$	forest cover loss in village i 1 years prior to the PKH	hectare
	$forestloss_{i,t}$	forest cover loss in village i the year of the first PKH implementation year	hectare
Other Covariates	$forest_{i,t}$	forest cover in village i in the beginning of the first PKH implementation year	hectare
	$roadlength_{i,2010}$	road length in village i in 2010	km
Selection Covariates	$eligiblepkh_{i,j,2007}$	PKH-eligible households in sub-district j where village i is located in 2007	number of households

Table 4: Matching Covariates: Extended Covariates

Variable Categories	Variable Name	Description	Unit
Outcome	$forestloss_{i,t+1}$	forest cover loss in village i one year post-PKH	hectare
Pre-Treatment Outcomes	$forestloss_{i,t-2}$	forest cover loss in village i 2 years prior to the PKH	hectare
	$forestloss_{i,t-1}$	forest cover loss in village i 1 years prior to the PKH	hectare
	$forestloss_{i,t}$	forest cover loss in village i the year of the first PKH implementation year	hectare
Other Covariates	$forest_{i,t}$	forest cover in village i in the beginning of the first PKH implementation year	hectare
	$roadlength_{i,2010}$	road length in village i in 2010	km
Selection Covariates	$eligiblepkh_{i,j,2007}$	PKH-eligible households in sub-district j where village i is located in 2007	number of households
	$health_{i,j,2007}$	access to health facilities in sub-district j where village i is located in 2007	indices
	$education_{i,j,2007}$	access to education facilities in sub-district j where village i is located in 2007	indices

Table 5: Fixed Effect Panel Regression Covariates

Variable Categories	Variable Name	Description	Unit
Dependent Variable	$forestloss_{i,t}$	forest cover loss in village i at time t	hectare
Independent Variables	$dpkh_{i,t}$	a dummy variable =1 if village i received the PKH at time t	binary
	$avgprecip_{i,t}$	yearly-average precipitation rate in village i at time t	mm/hr
	$avgtemp_{i,t}$	yearly-average surface air temperature in village i at time t	kelvin
Other Covariates	d_t	year dummies	binary
	a_i	village fixed effect	binary

Table 6: Covariates Balance: Core Covariates

Variable	**Matched**	**Mean Treated**	**Mean Untreated**	**Mean Differences**	**T-statistics**	**P-value**
Forest Loss 2006	Unmatched	10.2595	44.55416	34.29466	13.93052	0
	Matched	10.2595	12.13109	1.871594	1.518789	.1288351
Forest Loss 2007	Unmatched	11.97441	45.91605	33.94164	11.10039	0
	Matched	11.97441	10.67143	-1.302977	-1.15354	.2487058
Forest Loss 2008	Unmatched	12.59952	46.14196	33.54244	14.45814	0
	Matched	12.59952	13.37602	.7764965	.6825276	.4949152
Forest Cover 2008	Unmatched	745.3994	2535.41	1790.011	16.05271	0
	Matched	745.3994	773.2229	27.82349	.6415529	.5211726
Road	Unmatched	.7524126	1.173264	.4208516	14.01609	0
	Matched	.7523198	.7104826	-.0418372	-1.692646	.090542
PKH-eligible Households	Unmatched	746.4487	381.4517	-364.9969	-42.60677	0
	Matched	746.4487	733.41	-13.03868	-.8966042	.3699494

Table 7: Covariates Balance: Extended Covariates

Variable	**Matched**	**Mean Treated**	**Mean Untreated**	**Mean Differences**	**T-statistics**	**P-value**
Forest Loss 2006	Unmatched	10.2607	44.55214	34.29145	13.92866	5.82e-44
	Matched	10.2607	11.11492	.8542183	.7824803	.4339438
Forest Loss 2007	Unmatched	11.97577	45.914	33.93822	11.09884	1.44e-28
	Matched	11.97577	12.42443	.4486569	.317651	.7507537
Forest Loss 2008	Unmatched	12.60083	46.13995	33.53912	14.45613	3.31e-47
	Matched	12.60083	12.11863	-.4822009	-.4819464	.6298505
Forest Cover 2008	Unmatched	745.4449	2535.312	1789.867	16.05078	9.83e-58
	Matched	745.4449	753.9314	8.486456	.2004436	.8411362
Road	Unmatched	.7524126	1.173264	.4208516	14.01609	1.72e-44
	Matched	.7524126	.7123822	-.0400305	-1.618576	.1055579
PKH-eligible Households	Unmatched	691.8002	375.8529	-315.9473	-45.90971	0
	Matched	691.8002	682.127	-9.673162	-.9079567	.3639146
Health Facilities	Unmatched	.8646955	.8444506	-.0202449	-8.592148	8.94e-18
	Matched	.8646955	.8676227	.0029272	1.111534	.2663551
Education Facilities	Unmatched	.8538347	.8267677	-.027067	-12.61653	2.12e-36
	Matched	.8538347	.8572223	.0033876	1.54313	.1228187

Table 8: Fixed Effect Regression Results

Covariates	Without Matching			With Matching		
	Coefficient	95 % Confidence Interval		Coefficient	95 % Confidence Interval	
		LB	UB		LB	UB
PKH	-20.33*** (2.091)	-24.43	-16.23	-2.749** (1.310)	-5.318	-0.179
Precipitation	0.00278 (0.0225)	-0.0413	0.0468	0.0473*** (0.0168)	0.0143	0.0803
Temperature	0.190*** (0.0521)	0.0878	0.292	0.0937*** (0.0350)	0.0250	0.162
Constant	-29.59*** (9.458)	-48.13	-11.04	-24.38*** (6.285)	-36.71	-12.06
Observations	389,948			210,834		

Standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Fixed Effect with Year Dummies
Clustered SE at sub-district level

Table 9: Fixed Effect Regression Results: Extended Covariates

Covariates	Coefficient	95 % Confidence Interval	
		LB	UB
PKH	-2.917** (1.330)	-5.526	-0.307
Precipitation	0.0598*** (0.0192)	0.0221	0.0976
Temperature	0.0861** (0.0376)	0.0123	0.160
Constant	-26.13*** (7.363)	-40.58	-11.69
Observations	210,808		

Standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Fixed Effect with Year Dummies
Clustered SE at sub-district level

Table 10: Fixed Effect Regression Removing Immediate Neighbors

Covariates	Without Matching			With Matching		
	Coefficient	95 % Confidence Interval		Coefficient	95 % Confidence Interval	
		LB	UB		LB	UB
PKH	-19.81*** (2.089)	-23.90	-15.71	-3.058** (1.552)	-6.102	-0.0132
Precipitation	0.00780 (0.0216)	-0.0346	0.0502	0.0279* (0.0169)	-0.00512	0.0610
Temperature	0.219*** (0.0496)	0.122	0.316	0.0601 (0.0409)	-0.0201	0.140
Constant	-35.25*** (8.892)	-52.69	-17.82	-15.25** (7.486)	-29.93	-0.563
Observations	360,360			211,042		

Standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Fixed Effect with Year Dummies
Clustered SE at sub-district level

Table 11: Fixed Effect Regression Results: Removing Concessions and Protected Areas

Covariates	Without Matching			With Matching		
	Coefficient	95 % Confidence Interval		Coefficient	95 % Confidence Interval	
		LB	UB		LB	UB
PKH	-5.772*** (0.722)	-7.188	-4.357	-0.800* (0.443)	-1.670	0.0694
Precipitation	0.00747 (0.00872)	-0.00963	0.0246	0.0167*** (0.00560)	0.00574	0.0277
Temperature	0.0410** (0.0173)	0.00703	0.0750	0.0122 (0.0119)	-0.0111	0.0355
Constant	-7.959** (3.209)	-14.25	-1.667	-5.542** (2.161)	-9.780	-1.304
Observations	389,948			210,808		

Standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Fixed Effect with Year Dummies
Clustered SE at sub-district level

Table 12: Summary of the PKH's Impacts on Forest Loss

Specifications	**Without Matching**	**Matching on Core Covariates**	**Matching on Extended Covariates**
All	-20.33***	-2.749**	-2.917**
	(2.091)	(1.310)	(1.330)
Removing Neighbors	-19.81***	-3.058**	-1.48
	(2.089)	(1.552)	(1.384)
Removing Concessions and Protected Areas	-5.772***	-0.800*	-0.603*
	(0.722)	(0.443)	(0.364)

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Fixed Effect with Year Dummies
Clustered SE at sub-district level

2 Figures

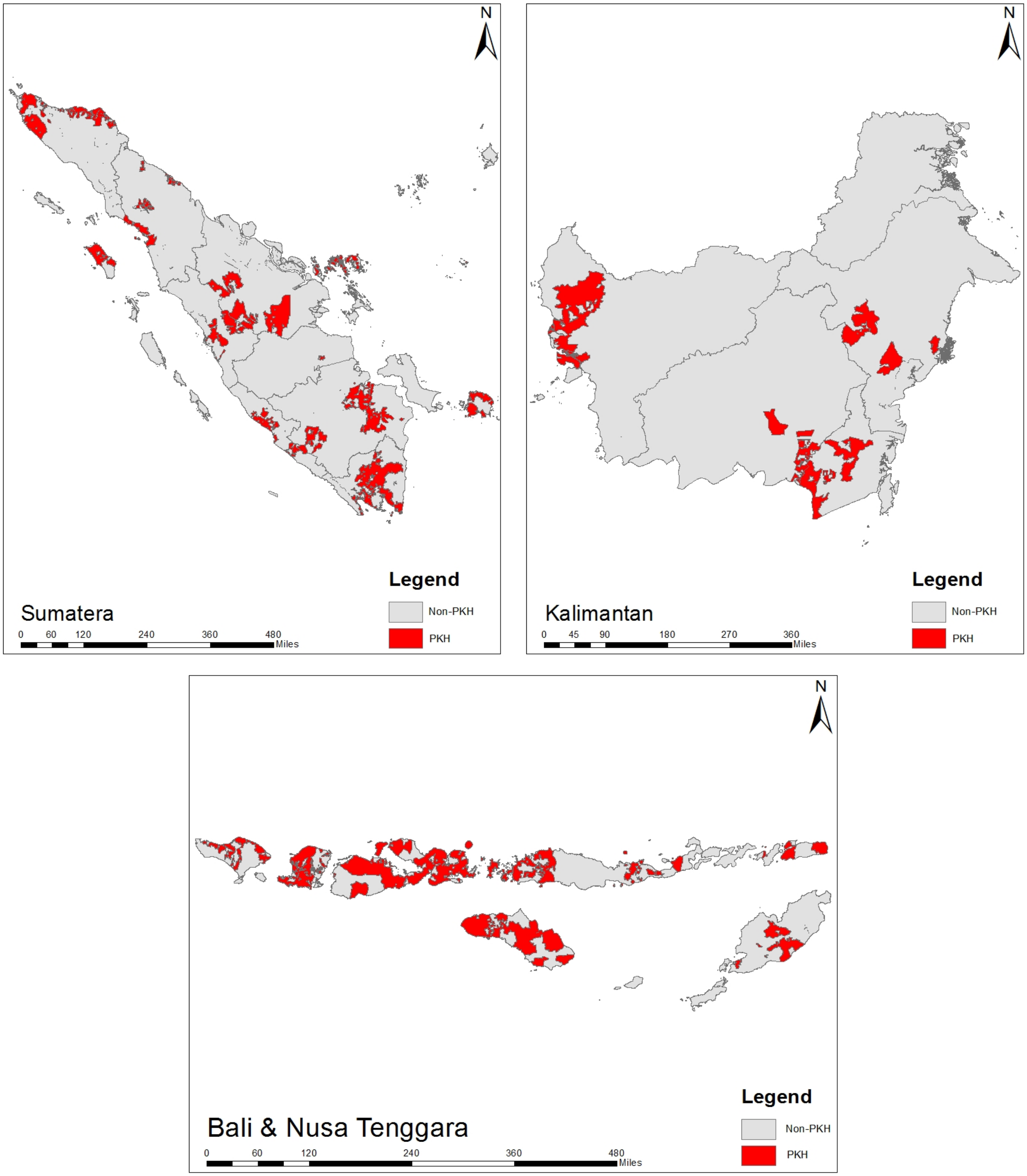

Figure 1: Spatial Distribution of the Program Keluarga Harapan (PKH)

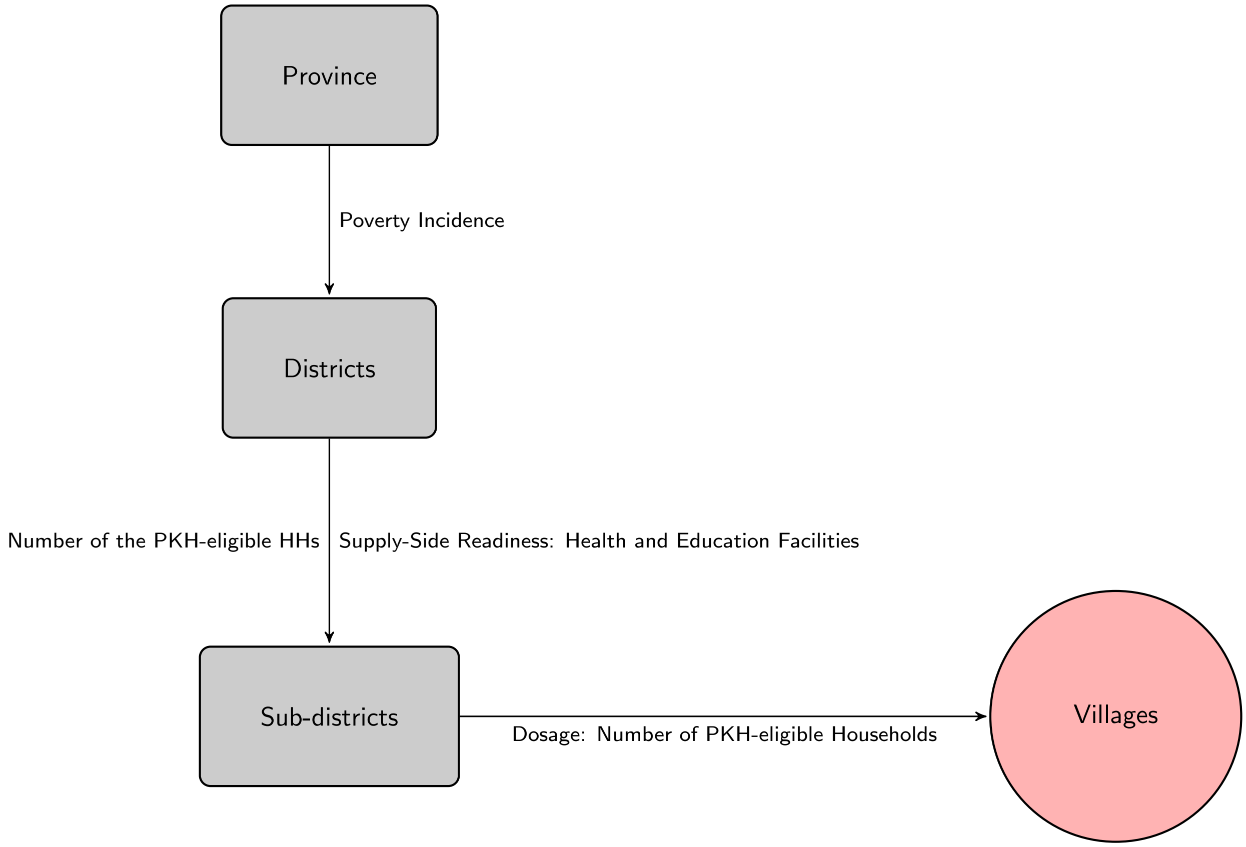

Figure 2: The PKH Assignment

Figure 3: Balance Criteria

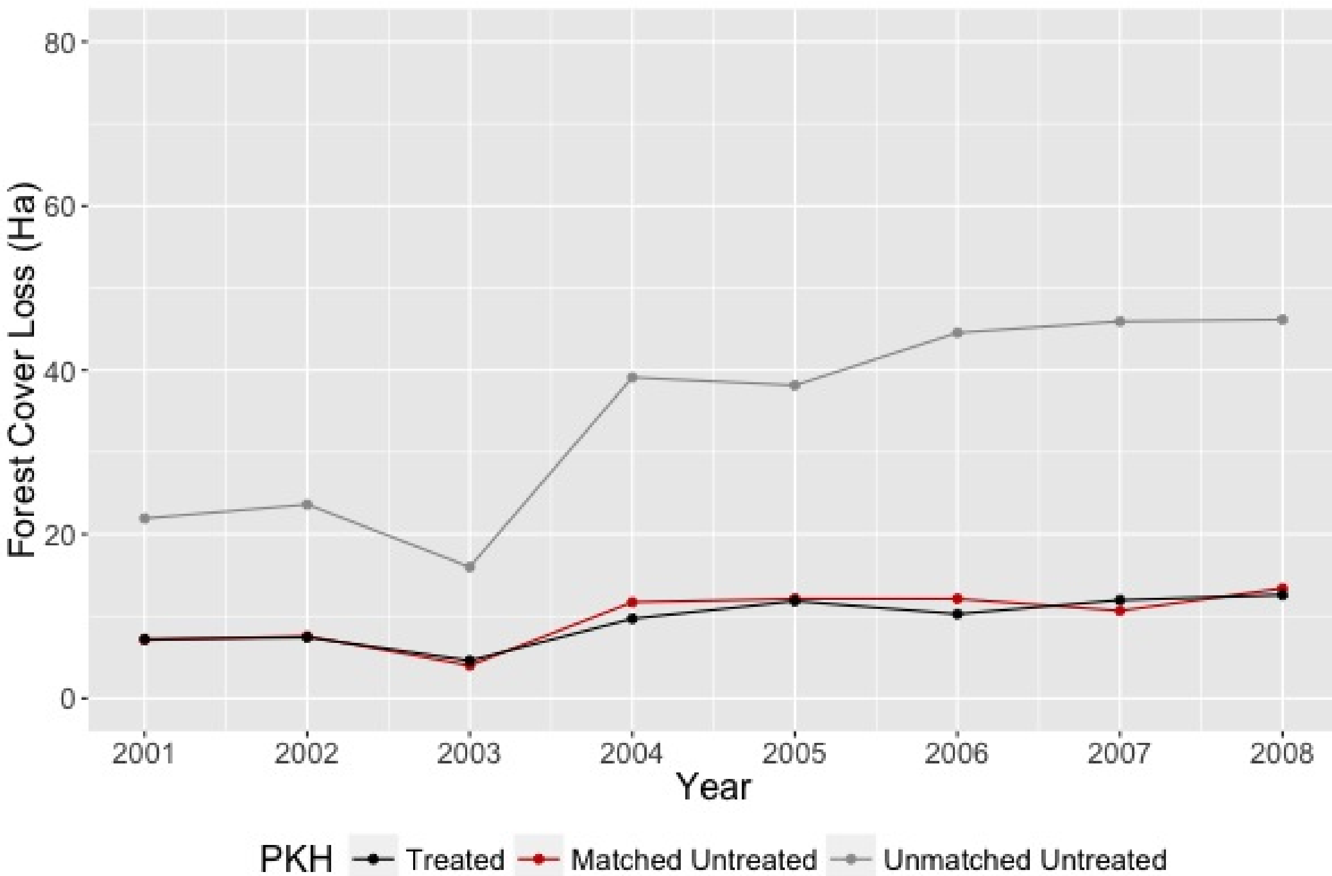

Figure 4: Forest Cover Loss 2001-2008

A Appendices

Table A.1: Covariates Balance 8 Provinces: Core Covariates

Variable	Matched	Mean Treated	Mean Untreated	Mean Differences	T-statistics	P-value
Forest Loss 2006	Unmatched	26.71695	86.3099	59.59295	7.822883	0
	Matched	26.71695	34.37171	7.654757	1.536512	.1245002
Forest Loss 2007	Unmatched	33.22309	91.87817	58.65509	6.145978	0
	Matched	33.22309	29.63981	-3.583279	-.8795552	.3791587
Forest Loss 2008	Unmatched	36.98162	84.80494	47.82332	7.027683	0
	Matched	36.98162	35.22335	-1.758275	-.4453308	.6561073
Forest Cover 2008	Unmatched	1883.642	5329.521	3445.879	9.104817	0
	Matched	1883.642	1915.749	32.10661	.1959322	.8446742
Road	Unmatched	1.219477	1.678283	.4588058	5.413051	6.35e-08
	Matched	1.219477	1.202506	-.0169706	-.2225064	.8239322
PKH-eligible Households	Unmatched	312.9884	277.9756	-35.01275	-4.391863	.0000114
	Matched	312.9884	310.0906	-2.897846	-.3142294	.7533649

Table A.2: Covariates Balance 8 Provinces: Extended Covariates

Variable	Matched	Mean Treated	Mean Untreated	Mean Differences	T-statistics	P-value
Forest Loss 2006	Unmatched	26.71695	86.3099	59.59295	7.822883	5.73e-15
	Matched	26.71695	32.85394	6.136986	1.419647	.1557967
Forest Loss 2007	Unmatched	33.22309	91.87817	58.65509	6.145978	8.28e-10
	Matched	33.22309	35.82876	2.605671	.5930636	.5531756
Forest Loss 2008	Unmatched	36.98162	84.80494	47.82332	7.027683	2.25e-12
	Matched	36.98162	34.07323	-2.90839	-.7795436	.4357105
Forest Cover 2008	Unmatched	1883.642	5329.521	3445.879	9.104817	1.05e-19
	Matched	1883.642	1878.136	-5.505926	-.0336242	.9731787
Road	Unmatched	1.219477	1.678283	.4588058	5.413051	6.35e-08
	Matched	1.219477	1.164024	-.0554527	-.7334926	.4633056
PKH-eligible Households	Unmatched	312.9884	277.9756	-35.01275	-4.391863	.0000114
	Matched	312.9884	303.1701	-9.818332	-1.078311	.2809667
Health Facilities	Unmatched	.8822269	.8167147	-.0655123	-12.50846	1.31e-35
	Matched	.8822269	.8815196	-.0007073	-.1256946	.8999807
Education Facilities	Unmatched	.8681085	.8520067	-.0161018	-3.385254	.0007141
	Matched	.8681085	.8724913	.0043828	.7832732	.4335179

Table A.3: Covariates Balance 5 Provinces: Core Covariates

Variable	Matched	Mean Treated	Mean Untreated	Mean Differences	T-statistics	P-value
Forest Loss 2006	Unmatched	41.4279	89.00741	47.5795	4.758501	0
	Matched	41.4279	55.85008	14.42217	1.586456	.1127983
Forest Loss 2007	Unmatched	51.1675	86.28387	35.11637	3.61221	.0003063
	Matched	51.1675	44.65277	-6.514733	-.9469321	.3437908
Forest Loss 2008	Unmatched	60.59305	94.10871	33.51567	3.351394	.0008094
	Matched	60.59305	57.31109	-3.281959	-.4757767	.6342868
Forest Cover 2008	Unmatched	2855.566	5700.035	2844.47	5.43333	0
	Matched	2855.566	2875.158	19.59244	.069084	.9449299
Road	Unmatched	1.609281	1.960525	.3512435	2.838239	.0045526
	Matched	1.609281	1.615815	.0065344	.0549057	.9562192
PKH-eligible Households	Unmatched	422.9969	348.1265	-74.87041	-6.290385	0
	Matched	422.9969	420.1149	-2.882051	-.2067682	.8362125

Table A.4: Covariates Balance 5 Provinces: Extended Covariates

Variable	Matched	Mean Treated	Mean Untreated	Mean Differences	T-statistics	P-value
Forest Loss 2006	Unmatched	41.4279	89.00741	47.5795	4.758501	2.00e-06
	Matched	41.4279	52.53367	11.10576	1.419202	.1560002
Forest Loss 2007	Unmatched	51.1675	86.28387	35.11637	3.61221	.0003063
	Matched	51.1675	56.6748	5.507298	.7346378	.4626485
Forest Loss 2008	Unmatched	60.59305	94.10871	33.51567	3.351394	.0008094
	Matched	60.59305	54.66072	-5.932326	-.9162698	.3596388
Forest Cover 2008	Unmatched	2855.566	5700.035	2844.47	5.43333	5.76e-08
	Matched	2855.566	2821.709	-33.85644	-.1192511	.9050887
Road	Unmatched	1.609281	1.960525	.3512435	2.838239	.0045526
	Matched	1.609281	1.559153	-.050128	-.4275894	.6689973
PKH-eligible Households	Unmatched	422.9969	348.1265	-74.87041	-6.290385	3.41e-10
	Matched	422.9969	405.3108	-17.68615	-1.30823	.1909497
Health Facilities	Unmatched	.8893344	.821049	-.0682853	-9.662135	6.46e-22
	Matched	.8893344	.8888892	-.0004451	-.0602789	.9519397
Education Facilities	Unmatched	.844399	.8444523	.0000534	.0076058	.9939318
	Matched	.844399	.8473937	.0029947	.3357275	.7371125

Table A.5: Fixed Effect Regression Results: Core Covariates

Covariates	Without Matching			With Matching		
	16 Provinces	8 Provinces	5 Provinces	16 Provinces	8 Provinces	5 Provinces
PKH	-20.33***	-37.76***	-47.89***	-2.749**	-13.39***	-16.22*
	(2.091)	(5.114)	(9.811)	(1.310)	(4.204)	(9.123)
Precipitation	0.00278	0.0965**	0.130**	0.0473***	0.227***	0.255***
	(0.0225)	(0.0482)	(0.0601)	(0.0168)	(0.0465)	(0.0680)
Temperature	0.190***	0.444***	0.310	0.0937***	0.295**	0.220
	(0.0521)	(0.148)	(0.218)	(0.0350)	(0.117)	(0.231)
Constant	-29.59***	-85.851***	-74.83**	-24.38***	-93.98***	-89.79***
	(9.458)	(24.20)	(34.30)	(6.285)	(18.57)	(31.35)
Observations	389,948	119,106	72,995	210,834	47,086	23,350

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Fixed Effect with Year Dummies
Clustered SE at sub-district level

Table A.6: Fixed Effect Regression Results: Extended Covariates

Covariates	**Without Matching**			**With Matching**		
	16 Provinces	**8 Provinces**	**5 Provinces**	**16 Provinces**	**8 Provinces**	**5 Provinces**
PKH	-20.33***	-37.76***	-47.89***	-2.917**	-13.09***	-16.58*
	(2.091)	(5.114)	(9.811)	(1.330)	(4.286)	(9.458)
Precipitation	0.00278	0.0965**	0.130**	0.0598***	0.269***	0.364***
	(0.0225)	(0.0482)	(0.0601)	(0.0192)	(0.0565)	(0.0860)
Temperature	0.190***	0.444***	0.310	0.0861**	0.242*	0.181
	(0.0521)	(0.148)	(0.218)	(0.0376)	(0.126)	(0.246)
Constant	-29.59***	85.81***	-74.83**	-26.13***	-96.25***	-108.7***
	(9.458)	(24.20)	(34.30)	(7.363)	(22.55)	(38.31)
Observations	389,948	119,106	72,995	210,808	47,086	25,350

Standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Fixed Effect with Year Dummies
Clustered SE at sub-district level

Table A.7: Fixed Effect Regression Removing Immediate Neighbors

Covariates	**Without Matching**			**With Matching**		
	16 Provinces	**8 Provinces**	**5 Provinces**	**16 Provinces**	**8 Provinces**	**5 Provinces**
PKH	-19.81***	-39.31***	-49.56***	-3.058*	-13.89***	-18.98**
	(2.089)	(5.109)	(9.915)	(1.552)	(4.837)	(10.52)
Precipitation	0.00780	0.108**	0.138**	0.0279*	0.207***	0.254***
	(0.0216)	(0.0460)	(0.0589)	(0.0169)	(0.0510)	(0.0722)
Temperature	0.219***	0.449***	0.394*	0.0601	0.188	0.113
	(0.0496)	(0.151)	(0.223)	(0.0409)	(0.159)	(0.327)
Constant	-35.25***	-89.03***	-88.79**	-15.25**	-74.27***	-73.91
	(8.892)	(24.03)	(34.56)	(7.486)	(25.99)	(47.76)
Observations	360,360	107,757	66,118	211,042	47,034	25,298

Standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Fixed Effect with Year Dummies
Clustered SE at sub-district level

Table A.8: Fixed Effect Regression Results: Removing Concessions and Protected Areas

Covariates	**Without Matching**			**With Matching**		
	16 Provinces	**8 Provinces**	**5 Provinces**	**16 Provinces**	**8 Provinces**	**5 Provinces**
PKH	-5.772***	-10.41***	-11.11***	-0.800*	-3.889***	-5.418**
	(0.722)	(1.532)	(2.529)	(0.443)	(1.174)	(2.502)
Precipitation	0.00747	0.0335*	0.0375*	0.0167***	0.0573***	0.0736***
	(0.00872)	(0.0199)	(0.0209)	(0.00560)	(0.0173)	(0.0240)
Temperature	0.0410**	0.139***	0.130**	0.0122	0.0617*	0.0200
	(0.0173)	(0.0425)	(0.0609)	(0.0119)	(0.0354)	(0.0730)
Constant	-7.959**	-27.60***	-27.41***	-5.542**	-21.96***	-19.66*
	(3.209)	(7.562)	(9.401)	(2.161)	(6.094)	(11.00)
Observations	389,948	119,106	72,995	210,808	47,060	23,350

Standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Fixed Effect with Year Dummies
Clustered SE at sub-district level

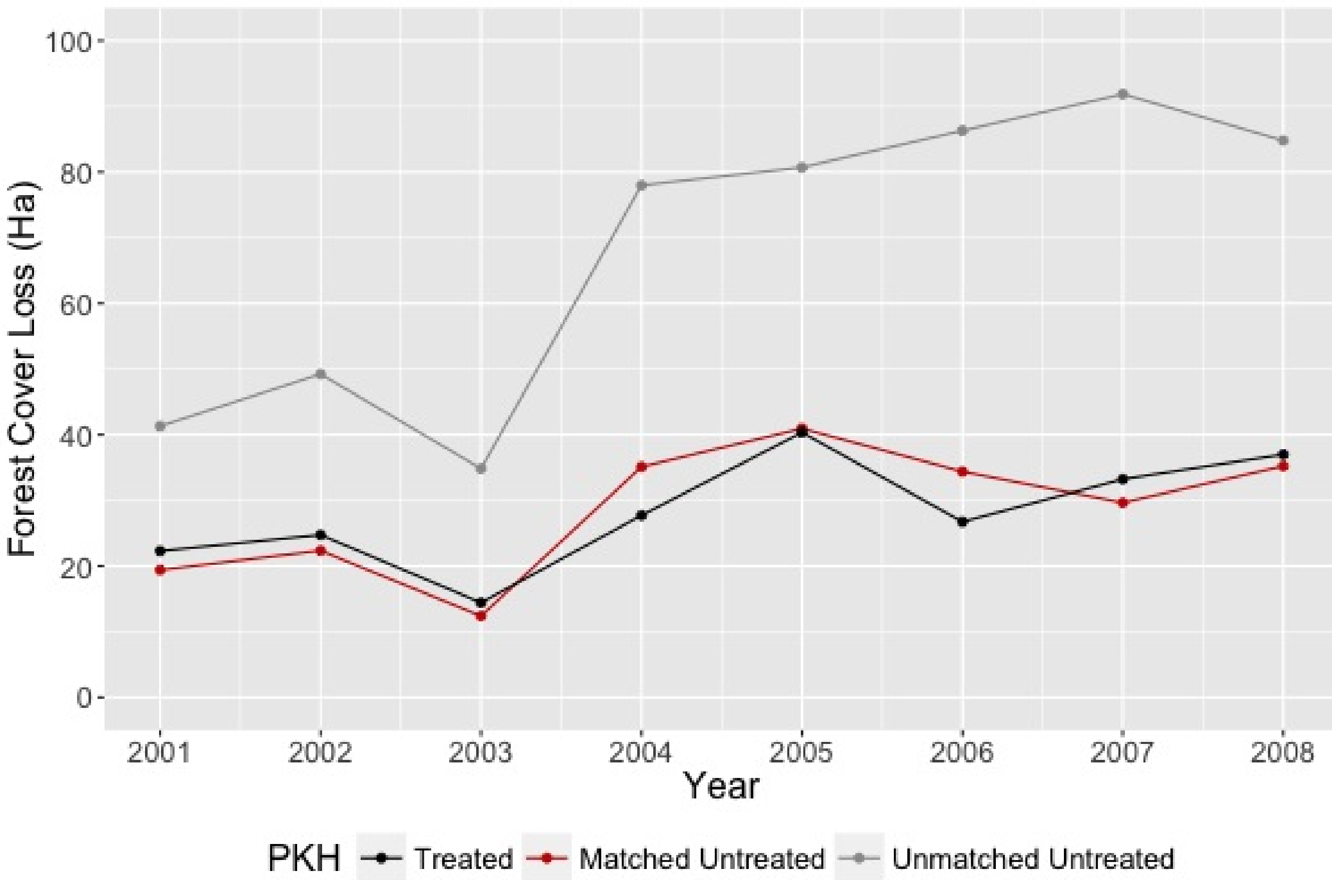

Figure A.1: Forest Cover Loss 8 Provinces

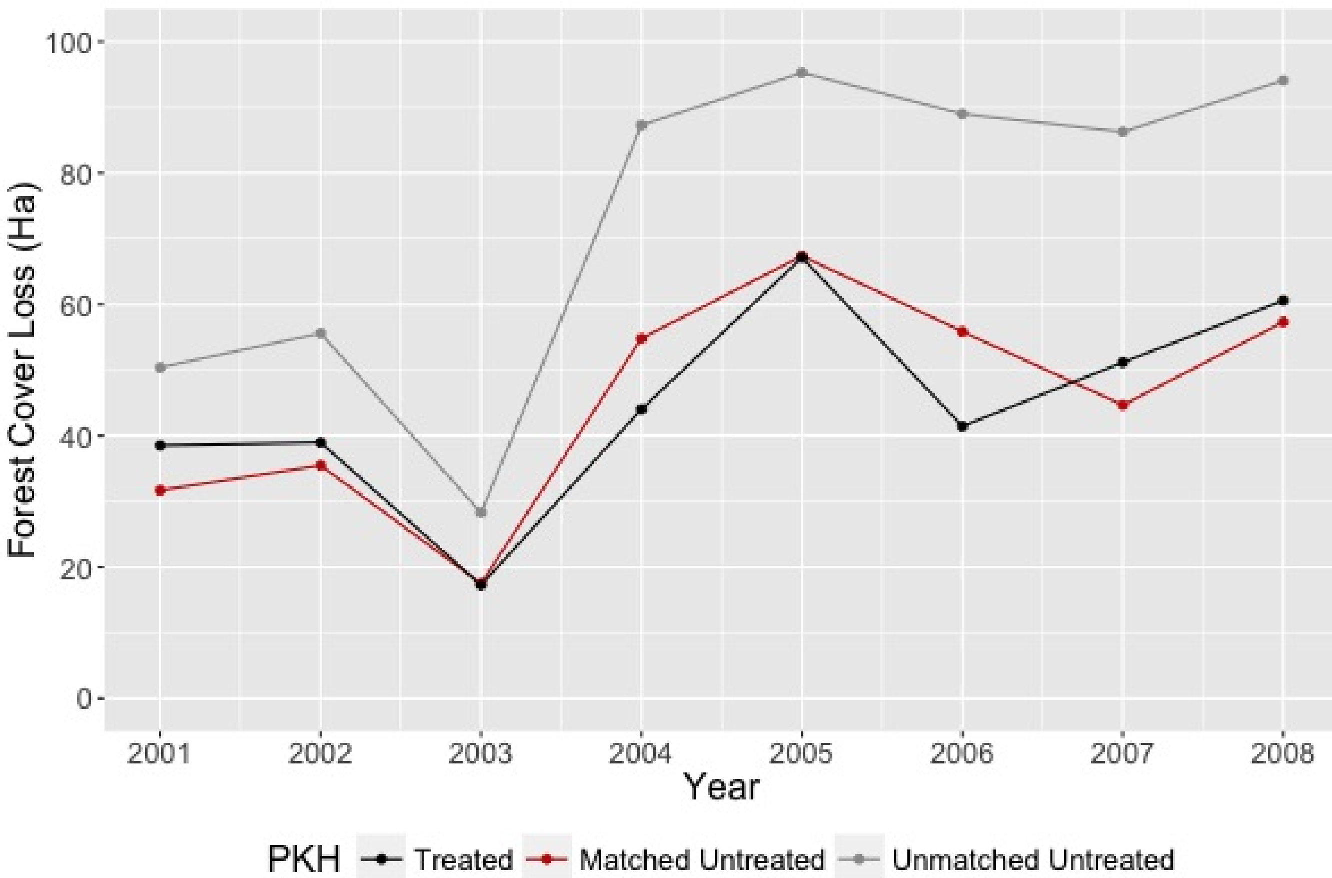

Figure A.2: Forest Cover Loss 5 Provinces