# Migration and The Incidence of Working Children: Evidence from Indonesia

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## INTRODUCTION

The primary aim of this paper is to examine the consequence of parents migration to working activities of their children in Indonesia. In order to do this, the method of Propensity Score Matching (PSM) is employed to address self-selection bias into migration before applying the probit model to estimate the significance of the effect.

The number of migrants in Indonesia has been increasing over time. Internationally, Indonesia is the country in Asia with the largest flow of documented migrants per year after the Philippines. In 2007, the World Bank estimated that Indonesia had as many as 4.3 million citizens working overseas (Bryant, 2005). Meanwhile, number of migrants internally has changed significantly and becomes more complex, larger in size and more advanced. About 5.5 million people were migrating inter-province during 2005-2010 which is increasing about 39 percent from the previous period (BPS,2011). In addition, the recent migration pathways do not follow the "step by step" path outlined by Skeldon (1990). They now can "jump" migrating from rural areas directly to mega cities, without moving first to small towns, cities, or big cities (Ananta and Arifin, 2008).

As increases in the volume and diversity of migration, the number of families fractured by migration is also growing tremendously. How migration affects the left-behind families is highly variable and complex (Yeoh, Hoang and Lam, 2010). Migration is considered as the importance strategy for enhancing the livelihood of sender family through remittances. At the same time, migration bring on a loss of local support on the family left-behind, especially children. For them, a migration envisioned as lack of a caregiver, especially when the migrants are the parents who are identified as the main source of a trust and help. Those children then become vulnerable from any harmful activities such as being abused or engaging in child worker.

Considering the working activities of children, the potentially effect of parents migration could be either positive or negative. The incidence of working children could be decreasing among migrant families due to the remittance receipt which may increase resources owned by household and release some household's financial burden (Yang, 2008; Park, Lee and deBrauw, 2010). Particularly for international migrant parents, the increased social protection

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among the 7-10 age cohorts can be attributed to increased knowledge about non-physical child discipline norms obtained and brought back by return migrants from abroad (Moran-Taylor, 2008). In contrary, labor supply of children could be increasing along with increasing the parents absence time as found by Booth and Tamura (2009) in Vietnam in 1990s. It might be happened in the initial period of paternal migration when the flow of remittance may be volatile and unreliable to ensure households resources or when the remittances has been mismanaged (Asis, 2000).

Working children in migrant families are also considered as a consequence of the adjustment of caring arrangement change due to the absence of one or both parents. Children, usually the older ones, are performing such domestic works for instance caring the younger siblings or other household work traditionally done by the former (father or mother), includes family farm business (Yeoh, Hoang and Lam, 2010; Parrenas, 2005).

The participation rate of children to market works in Indonesia decreased between 2000 and 2006, reaching 2.6%, before dramatically reversing in 2007. While the participation rate in 2006 was lower than in 2000, the rate in 2007 was double the rate in 2006. The suggestive explanation comes from IFLS (Indonesia Family Live Survey) 2000 and 2007 where a higher proportion of child workers in 2007 were mostly working solely inside their own household compared to 2000 and only about 1% were working both inside and outside the household (Sim, Suryadarma and Suryahadi, 2012).

One of main findings from Syukri, et.al, (2011) in Sukabumi and Cianjur suggests that kinds of work children perform are various. Some children are farm hands during harvest seasons, other children work on assembly home industries, and others undertake full time paid jobs or become domestic work. The last kind of work was significantly involved by most children in the study areas. In addition, the enrollment rate at high school level is significantly lower than at primary level for some reasons includes parents being migrant workers. It relates to existing condition where those study areas are migrant workers sending districts.

Despite the possibility of migration parents which lead to children performing working activities, only few studies that focus on this issue, especially in Indonesia. Some of those studies are Mansuri (2006) in Pakistan; Carlo, Chiquiar, and Salcedo (2012) in Mexico; and Booth and Tamura (2009) in Vietnam. Meanwhile, many studies of migration impact on children in Indonesia examine the outcome of health, education, and emotional well-being, but lack of examining their working activities (for example Deb and Seck, 2009 and Graham, et.al., 2012). Nguyen and Purnamasari (2011) investigate empirically how international migration and remittances in Indonesia affect child outcome and labor supply behavior in sending household. However, they eliminate the potentially effect of internal migration.

This study will contribute to the discourse of migration study in Indonesia by focusing in child worker as a consequence of not only international migration but also internal migration. As Indonesia government has already ratified the International Convention on the Protection of the Rights of All Migrant Workers and Members of Their Families (UU No.6 Tahun 2012), the empirical findings on any issue of migrants families are needed to suggest in what aspects the implementation of the convention in Indonesia should focus on.

The organization of this paper is as follows. The next section discuss the conceptual background of child labor and parents migration. We then detail our empirical strategy on section III after explain the data used. Section IV presents the estimation results and finally concludes in section V.

## BACKGROUND

### Why Children Work?

Theoretical and empirical literature concerning causes and consequences of child labor has been growing rapidly. This section aims to briefly review underlying theories that have been tested empirically in recent years. The ultimate objective of the review is to identify policies applied under various perceived causes of child labor.

Under the neoclassical models of household decision-making, parents view children as assets and they face quantity-quality tradeoff upon raising their children. Becker and Lewis (1973) argue that parents consider number of children and investment in human capital as substitutes and they diversify risk by sending some of their children to school and putting the others to labor market. Becker and Lewis (1973) also argue that child labor is complementary to other type of household capital. For example, investment in a family enterprise can be optimized if it is combined with labor from household's children; thus parents may prefer to send their children to labor market rather than to invest in children's education. Empirical evidence for this hypothesis have shown mixed evidence. Patrinos and Psacharopoulos (1997) in Brown et al. (2001) find that children in larger families perform worse in school and are less well-nourished, while Chernichovsky (1985) in Brown et al. (2001) find that family size raises educational attainment in Botswana. We may think that positive correlation between family size and schooling may occur due to diminishing marginal returns in household's production function, as large number of children available to engage in household work drives down the opportunity cost of schooling for a child in the family. Public policies that put constraints on options that parents can make for their children, such as minimum age of work and compulsory schooling are the typical policies induced by evidence on negative correlation between family size and educational attainment of children. Brown et al. (2001) argue that law of compulsory schooling and minimum age of work are not very effective, since supervision is costly. In fact, these policies can lead to proliferation of illegal child employment.

Another theory on the cause of child labor is the so-called *poverty hypothesis*, which basically states that child labor is a by-product of poverty and policy to reduce child labor should focus on economic development and increasing income (Brown *et al.*, 2001). Poverty hypothesis argues that parents send their children to work because they consider that return from education is not high enough to compensate for foregone income while children are in school. Preference for education also plays role in explaining the relationship between poverty and child labor, as poor parents are likely to appreciate return to education less than wealthy parents if poor parents themselves are not educated. Study by Priyambada et al. (2005) supports this view by showing that profile of child labor in Indonesia is closely related to the profile of poverty, and poverty is found as an important determinant of working for children. Priyambada et al. (2005) shows that like poverty in Indonesia, child labor is a rural phenomenon from households whose livelihood depend on agricultural sector, and is very determined by educational attainment of household heads. According to poverty hypothesis, child labor can be eliminated through poverty alleviation. Policy that joins the efforts to combat poverty and to reduce child labor includes giving cash transfers or in-kind gifts based on school attendance (PROGRESSA in Mexico, Program Keluarga Harapan or PKH in Indonesia, etc.) which successfully stimulates increase in enrollment and attendance at school.

The most recent literature on the theory of child labor stems from the perspective that child labor emerges as a response to market failure. The source of market failure may come from rigidity in market for adult labor or capital market failure. Basu (1999) in Brown et al. (2001) argues that child labor is the consequence of rigidity in market for adult labor which gives rise to adult unemployment. Households send their children to labor market to compensate for foregone income by unemployed adult. With regard to capital market failure, child labor emerges along with the possibility that households are liquidity constrained. Baland and Robinson (2000) in Brown et al. (2001) argue that child labor can be regarded as a form of household's loan from child's future income to finance the child's education today due to household's inability to access capital market. In other words, Baland and Robinson (2000) argue that for children, working and attending school can be performed simultaneously. This hypothesis is actually align with data from developing countries, where children work and attend school at the same time. Priyambada et al. (2005) mention that majority of child labor in Vietnam attend school and work in agricultural sector simultaneously because their workload at farms allow them to do so. Priyambada et al. (2005) also shows that half of the child labor aged 5-14 in Indonesia are still enrolled in schools, confirming the view that working does not always completely eliminate the opportunity for children to have formal education. With respect to this hypothesis, Brown et al. (2001) argue that policy aimed at improving labor-market function might lower incidence of child labor, as would government loan that is tied to child's educational performance or government's subsidy for education.

**Parental Migration and Labor Supply of Children**

Economic model of migration has been classified into two groups: one which emphasizes the individual determinants of migration, and the other which emphasizes household or family-level determinants of migration. Todaro (1969) predicts individuals migrate if income differentials are high enough and there are chances of getting employed; implying that migration is mainly driven by individual motivation and income disparity will induce migration. Human capital plays essential role in determining migrant selectivity based on Todaro (1969). On the other hand, family or household migration model by Mincer (1978) emphasizes family gain rather than personal gain to explain the cause of migration. Mincer (1978) argues that migration is the response of household to capital and insurance market imperfections and migrants provide additional financial sources for capital-constrained families. Family decides which member to participate in migration based on family gain rather than personal gain, and it may lead to intra-family bargaining between the appointed member and the rest of the family if personal gain is lower than family gain.

Theoretical literature has identified several channels through which migration may affect labor supply of children: 1) *remittance effect*, 2) *disruptive family effect*, and 3) *immediate substitution effect*. First of all, remittance sent by migrant parents may increase resources owned by household and release some of household's financial burden. If parents send their children to labor market in order to gain additional resources for household, remittance can actually substitute the income earned by children and there is no need for households to send children to labor market anymore. On the other hand, in the case where cost of education was once unaffordable, remittance will relax credit constrain of households and allow them to enroll their children in education. Children who were previously idle or helped their parents at farm may now participate in schooling. Secondly, departure of parents in migrant households may cause children to have no role model in their critical growing period, or requires children to perform additional household responsibilities. Household with migrating parents face geographic separation which causes loss of manpower, which in turn could affect decision-making process at households. In the initial period of parental migration when parents are not settled yet in the migration destination, flow of remittance may be volatile and unreliable to ensure household resources. Thus, parental migration increases possibility of children (especially the older ones) to join labor market to compensate for foregone income. Lastly, parental migration may also induce future migration by household member, including children. Due to information and network effects, having a migrant parent increases the likelihood that children themselves will become migrant and it discourages child schooling at the origin. Possibility to migrate in the future can influence the expected return to education even if children migrate at the age older than the age when they would be attending schools. Consequently, possibility to migrate in the future will lower the expected returns from schooling. In summary, the net-effect of parental migration on labor supply of children depends on the cumulative magnitude of the aforementioned effects.

Empirical literature has documented mixed evidence related to the impact of parental migration on the labor supply of remaining children. Using Vietnam Living Standard Survey, Booth and Tamura (2009) examines the impact of father's temporary absence on children left behind in terms of their school attendance, household's expenditure on education, and non-housework labor supply by focusing on 7-18 years old children. By focusing on households with paternal temporary absence and maternal presence, Booth and Tamura (2009) finds that paternal temporary absence increases son's non-housework labor supply and the impact is larger if absence is longer. Interestingly, this study doesn't find evidence on the impact of paternal absence on school attendance and education expenditure. This finding suggests that boys' labor are more substitutable for fathers' labor supply and Vietnamese children do not sacrifice schooling if they decide to join labor market. Study by Nguyen and Purnamasari (2011) using Indonesia Family Life Survey (IFLS) 2000 & 2007 finds that gender matters in determining the impact of international migration and remittances on child outcomes and labor supply. Nguyen and Purnamasari (2011) find that male migrant reduces working hours of remaining household members. Meanwhile, female migration only reduces non-housework labor supply by children, presumably due to the fact that migrant women have stronger bargaining power over investment choices related to children within a household. Nguyen and Purnamasari (2011) do not find any impact of migration on children's school enrollment, implying that reduction in non-housework labor supply doesn't coincide with improvement in school enrollment.

**Selection and Causation**

Empirical literature in migration has long been suffered from the issue of selection bias. And there is an intensified interest in addressing self-selection in recent years, particularly with respect to establishing the true causal relationship. In our study, the difficulty in assessing the impact of migration is mainly caused by the fact that migrant and decision to leave children at origin are not randomly dispersed across individuals or households. Source of selection may come from different aspects, such as welfare, health, cohort, gender, etc. In the case that migration is costly, it tends to select wealthy households because they are the only one who could afford the migration cost and they probably know better about migration network. If we believe that migration in Indonesia positively selects those from wealthier households, then we must remove the selection first to come at unbiased causal relationship between migration and child labor activity in remaining households. If migration selects a pool of relatively wealthier households, then it is unlikely for children from these particular households to engage in child labor activity because parental migration tends to be more successful and there is very low need for children to perform non-housework activity to compensate for foregone income at initial period of parental migration. On the other hand, migrant workers from Indonesia are dominated by women. Maternal migration may bring different consequences compared to paternal migration, considering that mother has a more nurturing role and also they are likely to prioritize education of their children. Migrant mother tends to be shorter in terms of duration, hence it is less likely to create intention for children to participate in migration. Departure of mother may cause children to do house chores because person who once was responsible to do housework is now not around. If migration selects women more than men, then it is more likely that migration increases housework activity of children at the origin only because the fact that women dominates the pool of migrants, and not necessarily explaining the true impact of migration.

The objective of this study is to examine the impact of migration on the labor supply of children who do not participate in the migration itself. Migration and decision to leave children at the origin are considered to be household-level intervention. Within a household, parent may choose which children to bring along in the migration, and which children they decide to leave. That being said, decision to leave children at the origin is not randomly allocated among households and selection is likely. Parent may decide to leave children if children are too young and there is a member of the family that could take care of their children during migration. In the case that children who are left behind are dominated by relatively younger children, of course parental migration will give no impact on the likelihood of children actively participate in labor market since their age constrains them to do so. This self-selection poses a severe challenge to ascertain the impact of migration on labor supply of children at the origin. Consequently, this study should take potential selection bias into account to come up with unbiased result. In this case, OLS estimate is unable to reveal the true causal relationship.

## DATA AND METHODOLOGY

### Data

The dataset that we employ is Indonesia Family Life Survey (IFLS) wave 3 (2000) and wave 4 (2007). IFLS is the continuing longitudinal socioeconomic and health survey. It is based on a sample of households representing about 83% of the Indonesian population living in 13 of the nation's 26 provinces in 1993. The survey collects data on individual respondents, their families, their households, the communities in which they live, and the health and education facilities they use. The first wave (IFLS1) was administered in 1993 to individuals living in 7,224 households. IFLS2 sought to re-interview the same respondents four years later. A follow-up survey (IFLS2+) was conducted in 1998 with 25% of the sample to measure the immediate impact of the economic and political crisis in Indonesia. The next wave, IFLS3, was fielded on the full sample in 2000. IFLS4 which is employed in this study was fielded in late 2007 and early 2008 on the same 1993 households and their split-offs; As many as 13,535 households and 44,103 individuals were interviewed (Strauss, et al, 2009). Overall, the IFLS iteration rate is high, and it represents one of the first efforts in social surveys to track migrants, which permits studying the migration as a dynamic process.

The IFLS provides the rich information both on children and migration. However, the survey is not designed to study migration issues and hence provide limited information on a small group of migrants. For instance, there are no specific questions asking about the children condition on migrant household. However, there is a specific module on parental information (B5-BAA) which ask the location of their parents live. The left behind children are defined as those whose parents (at least one) is/are reside not within the same village as they do.

Child worker has many different definition. IFLS added a particular module on working activities of children (B5-DLA). Those activities are divided into four category: working for wage, working for family farm business, working for family non-farm business, and special for IFLS4, the module records the household works. In this paper, we differentiate the outcome into two types of child worker. First, child who is engaged in any kinds of working activities in the past month. Second, child who is engaged in economic work in the past month, either inside (farm or non-farm family business) or outside household (work for wage) so we exclude the domestic worker children.

Those two modules are administered to children aged below 15 years old. Because we need to explore the children and the household condition in 2000 as base line, we limit the observation of children aged between 7-14 years old in 2007. The definition of children here is only by the age without considering their status in the household.

## Methodology

This study implements Propensity Score Matching (PSM) to create comparable control group that resembles the treatment group with respect to probability to participate in migration or to receive remittance based on a number of observable characteristics. PSM is first applied on household-level data to ensure for balanced sample. According to Dehejia and Wahba (2002), matching on the propensity score is essentially a weighting scheme, which determines what weights are placed on comparison units when computing the estimated treatment effect. Essentially PSM estimator is simply the mean differences in outcomes over the common support, appropriately weighted by the propensity score distribution of participants (Caliendo and Kopeinig, 2005). Matching puts the emphasis on observations that have similar observable characteristics, and so those observations on the margin might get no weight at all (Blattman, 2010). A weighted regression of outcome on treatment is thus a comparison of means across treatment and control groups, but the control group is reweighted to represent the average outcome that the treatment group would have exhibited in the absence of treatment (Nichols, 2008). Once the weights are obtained from PSM for each household in the observation, the model is estimated using weighted regression. Since the outcome of interest is at individual level, standard errors are clusterized at household level to count for the fact that individuals belong to same household are correlated. Migration and remittance are considered as treatments at household level and household samples are divided into separate treatment group and control group: treatment group includes 824 children who are left behind during parental migration, while the control group 1544 children who also brought along during parental migration.

The major practical problem of matching arises when there are numerous differences between treated and untreated units to control for. The solution proposed by Rosenbaum and Rubin (1983) to the dimensionality problem is to calculate the *propensity score*, which is the probability of receiving the treatment given X, noted as $P(D = 1 \mid X)$, or simply $p(X)$. Rosenbaum and Rubin (1983) prove that when it is valid to match units based on the covariates X, it is equally valid to match on the propensity score. In other words, the probability of participation summarizes all the relevant information contained in the X variables. The major advantage realized from this is the reduction of dimensionality, as it allows for matching on a single variable (the propensity score) instead of on the entire set of covariates. In effect, the propensity score is a balancing score for X, assuring that for a given value of the propensity score, the distribution of X will be the same for treated and comparison units. To implement PSM, there are two assumptions that must be satisfied: 1) Conditional Independence Assumption (CIA or unconfoundedness) and 2) Common Support. The CIA assumption based on propensity score states that given the probability for an individual to participate in a treatment given his observed covariates X, potential outcomes are independent of treatment assignment:

$$Y\ (0), Y\ (1)\ D \mid P(X), \forall\ X$$

This is a strong assumption as it implies that selection into treatment is solely based on observable characteristics and that all variables influencing treatment assignment and potential outcomes simultaneously are observed. A further requirement besides independence is the common support or overlap condition. Matching seeks to mimic the identification of randomization by balancing key covariates that jointly determine selection into treatment and outcomes. It rules out the phenomenon of perfect predictability of D given X:

$$0 < P(D = 1|X) < 1$$

This assumption ensures that persons with the same X values have a positive probability of being both in treated group and control group. Covariate balance is implicit under randomization because each unit of the experimental sample has an equal probability (or more generally, a probability that is known to the experimenter) of being assigned to treatment or control. Therefore, treatment is assigned independent of potential outcomes Y (1) and Y (0) under treatment (T = 1) and control (T = 0), respectively. In the absence of a treatment, one would expect similar average outcomes from both groups. Similarly, if both groups were to receive (the same) treatment, one would expect similar average outcomes from both groups. In other words, by ensuring that the distributions of key covariates are balanced across treatment and control groups, similar methods to those used in randomized experiments can be used to estimate ATT on matched datasets. Given that both CIA and common support hold, PSM estimator for ATT can be written as:

$$\tau_{ATT}^{PSM} = E_{P(X)|D=1}\{E[Y(1)|D = 1, P(X)] - E[Y(0)|D = 0,\ \ P(X)]\}$$

Once observations in treated and control group are matched based on propensity score proximity, differences in outcomes (child labor supply) between the two can be considered as the impact of migration.

**Propensity Score Estimation**

First step in PSM is to predict propensity score of participation into treatment. In general, little advice is available regarding which functional form to be used to predict propensity score. Caliendo and Kopeinig (2005) argue that for binary treatment case, where we estimate the probability of participation vs. non-participation, logit and probit models yield similar results. Hence, the choice is not too critical, even though the logit distribution has more density mass in the bounds. More advice is available regarding covariates to be included in the propensity score model. The choice of variables should be based on economic theory and previous empirical findings, and only variables that influence simultaneously the participation decision and the outcome variable should be included. These variables should either be fixed over time or measured before participation to ensure that they are unaffected by participation or anticipation of participation. Caliendo and Kopeinig (2005) argue that although the inclusion of non-significant variables will not bias estimation, it can increase the variance.

I identify several covariates that jointly influence parent's decision to leave children and children's participation in labor market. These covariates are used in the analyses to control for the observable differences between treated and control group, therefore, isolating the impact of being left behind. Since PSM only allows covariates that are measured before participation into treatment, we only take into account time-invariant covariates and time-variant covariates whose values could be re-estimated as of time before migration given that information of migration duration is available.

**Table 1. Probability for Children in Migrant Households to be Left Behind**

| **Variable** | **Coefficient** | **Standard Errors** | **P > \|z\|** |
|---|---|---|---|
| Gender dummy: boys | 0.146 | 0.055 | 0.008 *** |
| Age of children | -0.646 | 0.057 | 0.000 *** |
| Rural | -0.421 | 0.059 | 0.000 *** |
| Household size | -0.117 | 0.058 | 0.045 *** |
| Quartile PCE | -0.088 | 0.028 | 0.002 *** |
| Dependency ratio | -0.398 | 0.057 | 0.000 *** |
| Provincial dummy: Java | 0.405 | 0.071 | 0.000 *** |
| Provincial dummy: East | 0.301 | 0.088 | 0.001 *** |

N = 2368, Pseudo $R^2$ = 0.0956 , LR test (prob) = 292.63 (0.000) ***

*** Significant at 1%

All covariates in Table 1 are statistically significant in determining probability for children in migrant households to be left behind, and all of them are showing the sign as predicted by theory or by previous findings. Among children in migrant households, boys are more likely to be left behind compared to girls. On the other hand, children with older age decrease the probability to be left behind. With respect to characteristic at household level, household with bigger size are less likely to leave children behind

**Matching**

The choice of proper algorithm is very important in this study given the small size of dataset. This section is dedicated to provide preliminary assessment of each algorithm considered and to assess balance across all covariates in treated and control group.

The sample consists of 824 treated children and 1544 control children. Density distribution of propensity score in both groups shows substantial overlap in each value of propensity score. Therefore, common support assumption required to apply PSM is satisfied. However, propensity score distributions are not similar in the treatment group and control group, as can be seen in Figure 1: there are a lot of treated observations with high propensity score and a lot of untreated observations with low propensity score. Table 2 provides information on performance of each matching algorithm.

**Figure 1. Propensity Score Distribution Before Matching**

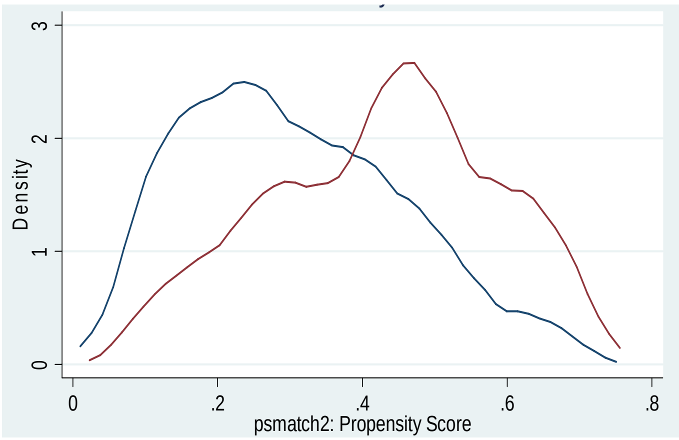
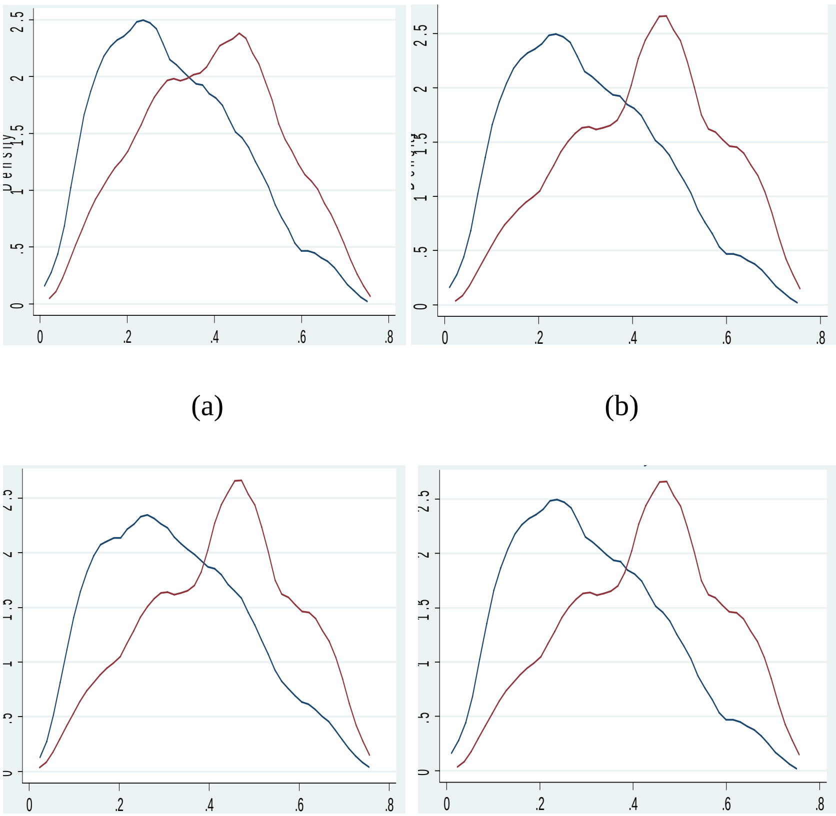


**Table 2. Performance Comparison of Different Matching Algorithm**

| Algorithm | Average P-Score for Treated | Average P-Score for Control | Number of Treated used to Match | Number of Control used to Match |
|---|---|---|---|---|
| (Before Matching) | 0.426 | 0.307 | 824 | 1544 |
| NN without replacement, caliper (0.001) | 0.392 | 0.392 | 626 | 626 |
| NN with replacement, caliper (0.001) | 0.423 | 0.341 | 795 | 226 |
| 5-NN matching with caliper, (0.001) | 0.423 | 0.325 | 795 | 875 |
| Kernel, bandwidth (0.001) | 0.423 | 0.324 | 795 | 1325 |

NN matching without replacement produces highest quality of match at the cost of discarding too many observations. Since there are a lot of treated observations with high propensity score and only few control observations with high propensity score, using NN matching with replacement reduces the number of controls used to construct the counterfactual outcome (Caliendo and Kopeinig, 2005). K-nearest neighbor matching with 5 neighbors uses more information but at the cost of lower quality of matching compared to NN without replacement. Kernel matching uses almost all of the control units within the bandwidth to build counterfactual. Compared to the performance of NN matching, they result in lower variance but at the cost of high increase in bias. Figure 2 contrasts propensity score distribution after matching for each of the algorithm discussed.

**Figure 2. Propensity Score Distribution After Matching**



(a) (b)

(c) (d)

Upper panel: (a) NN-matching without replacement and caliper (0.001), (b) NN-matching with replacement and caliper (0.001). Lower panel: (c) 5-NN matching with replacement and caliper (0.001), (d) kernel matching with bandwidth (0.001)

---------- : propensity score distribution for untreated (control)

---------- : propensity score distribution for treated

Visual comparison fails to show obvious difference in terms of propensity score distribution. As we can see that none of the algorithm is able to produce perfect match and matching produces little changes in terms of distribution of propensity scores. NN matching without replacement produces highest quality of matching, as distribution of propensity score in two groups after matching are most alike. But it comes at high cost of discarding too many variables, therefore increased variance. We decide to use 5-NN matching as primary algorithm in this case, as it still performs better compared to radius in terms of bias reduction.

To ensure that matching procedure is able to balance distribution of covariates used in predicting propensity score in both control and treatment group, we are going to perform two sample t-tests after matching. When two-sample t-test is used, we compare differences in covariate means for both groups after matching. Before matching differences are expected, but after matching the covariates should be balanced in both groups and hence no significant differences should be found. Table 3 summarizes balancing test for PSM.

**Table 3. Balancing Test for PSM**

| Variable | Sample | Mean Treated | Mean Control | Difference | P > \|t\| | Sig. |
|---|---|---|---|---|---|---|
| Gender dummy: boys | Unmatched | 0.506 | 0.470 | 0.036 | 0.096 | * |
| | Matched | 0.506 | 0.510 | -0.004 | 0.837 | |
| Age of children | Unmatched | 0.269 | 0.522 | -0.253 | 0.000 | *** |
| | Matched | 0.273 | 0.281 | -0.008 | 0.713 | |
| Dummy for rural | Unmatched | 0.657 | 0.519 | 0.138 | 0.000 | *** |
| | Matched | 0.653 | 0.666 | -0.013 | 0.574 | |
| Household size | Unmatched | 0.404 | 0.445 | -0.041 | 0.052 | ** |
| | Matched | 0.397 | 0.401 | -0.004 | 0.873 | |
| Quartile PCA | Unmatched | 2.020 | 2.188 | -0.168 | 0.000 | *** |
| | Matched | 2.032 | 2.003 | 0.029 | 0.575 | |
| Dependency Ratio | Unmatched | 0.442 | 0.593 | -0.151 | 0.000 | *** |
| | Matched | 0.452 | 0.469 | -0.017 | 0.466 | |
| Provincial dummy: Java | Unmatched | 0.635 | 0.549 | 0.086 | 0.000 | *** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Matched | 0.658 | 0.680 | -0.022 | 0.335 | |
| Provincial dummy: East | Unmatched | 0.203 | 0.183 | 0.02 | 0.252 | |
| | Matched | 0.179 | 0.163 | 0.016 | 0.368 | |
| * Significant at 10%, ** Significant at 5%, *** Significant at 1% | | | | | | |

As can be seen from Table 3, there is clear evidence of covariate imbalance between groups before matching. This means that selection occurs and PSM can help in balancing covariates across control and treated groups. The results from the test of equality of means for the matched sample are shown under label 'matched'. Clearly, after matching the differences are no longer statistically significant, suggesting that matching has successfully reduced biased associated with selection from observable characteristics.