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Effects of health insurance on labour supply Evidence from the Health Care Fund for the Poor in Viet Nam

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Abstract

The expansion of health insurance in emerging countries raises concerns about unintended negative effects of health insurance on labour supply. This paper examines the labour supply effects of the Health Care Fund for the Poor (HCFP) in Vietnam in terms of the monthly number of work hours and the probability of employment. Employing Difference-in-Differences Matching methods on the Vietnam Household Living Standard Survey 2002-2006, we show that HCFP, which aims to provide poor people and disadvantaged minority groups with free health insurance, has a positive labour supply effect in the short run. However, in the longer run, the net effect becomes negative due to the income effect. This is manifested in both average work hours per month and the probability of employment albeit the effect on the latter is statistically insignificant. Interestingly, the finding of the income effect is mainly driven by the non-poor recipients living in rural areas. This raises the question of targeting strategy of the programme to avoid unintended labour supply distortion.

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1 Introduction

The expansion of public health insurance to the poor and the vulnerable has received a large amount of attention because of their potential effects on reducing catastrophic out-of-pocket spending and increasing access to health care (Lagomarsino et al., 2012). These impacts are particularly important for the poor who normally cannot afford to pay out-of-pocket. These goals are especially desirable for many low and middle income countries with a large proportion of poor population who normally do not have the financial resources to buy health insurance (ibid.).

Many emerging economies in Asia, Latin America and Africa are making progress towards Universal Health Coverage (UHC) to reduce the financial hardship for those seeking health care (Rodin and de Ferranti, 2012; Lagomarsino et al., 2012). The momentum on achieving UHC is rather strong as many countries have increased or committed to increase government spending on total health expenditure (Lagomarsino et al., 2012). The ambition towards UHC has also received support and active participation from important donors and international organizations (ibid.).

However, there have been concerns about unintended labour market consequences of health insurance in general and health insurance for the low income in particular. For instance, it is shown that social health insurance expansion in East Europe and Central Asia during 1990-2004 has been associated with higher unemployment (Wagstaff and Moreno-Serra, 2009) and reduced aggregate employment (Wagstaff and Moreno-Serra, 2015) while increasing the aggregate share of self-employment (ibid.). Even though the authors failed to control for political changes which potentially caused unemployment, their findings provoked some thoughts on the potential negative impacts of health insurance on the labour market. From a theoretical perspective, the theory of static labour supply (Chou et al., 2002; Rosen, 2014) predicts a negative labour supply effect of health insurance which is not tied to employment due to the income effect.

In the context of the UHC movement, there has been a renewed interest in the labour supply effects of health insurance. However, there is currently inadequate and inconclusive evidence on the topic. A systematic review on the topic (Lê et al., 2017) suggests that empirical evidence in low and middle income countries is relatively scarce and sporadic probably due to data limitation. The existing literature on the labour supply effects of pro-poor health insurance programmes is mainly represented by studies on the American healthcare system where the evidence is mixed (ibid.). Whereas, the evidence beyond the US is very limited (Lê et al., 2017). This creates a knowledge gap, especially in low and middle income countries where health insurance coverage is expanding. Therefore, to fill this gap, it is necessary to seek for more evidence to guide policy making.

In Vietnam, this is crucially relevant as health coverage is being expanded rapidly with assertive political commitment which has been translated into recent legal documents such as the Health Insurance Law versions in 2008 and 2014. In a latest strategic document, the government aims at a coverage rate of more than 90 percent by 2020 (Socialist Republic of Vietnam, 2016).

This paper investigates the effects of the Health Care Fund for the Poor (hereafter, HCFP) on the labour supply of the beneficiaries in Vietnam. Using pre-treatment matching techniques combined with a Difference-in-Differences approach on a panel of Vietnam Household Living Standard Survey during 2002-2006, we evaluate the labour supply effects of the programme in terms of monthly work hours and the probability of

working. We separate the effects for urban and rural individuals as well as the poor and non-poor people among the treated individuals. This paper contributes to filling the knowledge gap on the impact of health insurance on the labour supply and presents empirical evidence on this sporadically researched topic in the context of low and middle income countries.

2 Literature Review

The distorting effect of health insurance and welfare benefits have been discussed thoroughly in theory. The budget constraint approach argues that government-provided health insurance, as financed by tax, is similar to a welfare benefit and hence can be considered as a positive income shock for low income individuals and those who have high health expenses (Boyle and Lahey, 2010). Therefore, a non-contributory health scheme may discourage these individuals to work due to the income effect.

Similarly, the static labour supply theory states that individuals make a trade-off between labour supply and leisure at a given wage level (Chou and Staiger, 2001; Rosen, 2014). Therefore, the provision of welfare benefits increases household income but also potentially reduces labour force participation (Rosen, 2014). Importantly, as argued by Chou and Staiger (2001), the income effect of non-contributory health insurance may be stronger than that of other welfare benefits as it not only increases income (in the form of the subsidy) but also reduces variation in consumption resulting from the removal of unexpected catastrophic health expenses. Therefore, compulsory health insurance which is not tied to employment may make paid work less attractive thanks to the consumption smoothing (Chou and Staiger, 2001). The magnitude of the income effect however depends on the share of health expenses in total household expenses (ibid.).

Despite being used widely, the theories implicitly implies a broad definition of welfare benefits which also include public health insurance. Therefore, the income effect of health insurance is viewed similarly as that of other social transfers which normally have a more direct income push. In the context of low and middle income countries, this direct income effect of public health insurance is not always obvious as in the case of cash transfers due to the negligible health premiums of many public schemes (e.g. in Vietnam the premium of health insurance for the poor under HCFP was only more than 2 USD in 2003 (Socialist Republic of Vietnam, 2002)). Besides, the removal of catastrophic health costs are not always warranted as it depends on the breadth and depth of the coverage.

In addition, there are concerns about moral hazard arising from welfare programmes, Gruber (2010) argues that non-contributory welfare provision is negatively correlated with labour supply as it 'raises the incentive for individuals to be poor' in order to qualify for the benefits (Gruber, 2010, p.500). It is important to note that Gruber's definition refers to the American welfare system wherein welfare benefits also concern in-kind transfers like medical care (Gruber, 2010, chapter 17). Therefore, his argument is not only applicable to in-cash and in-kind transfers but also health insurance for the poor, particularly Medicaid in the US. Even though this view has been considered debatable (Banerjee et al., 2015), it seems consistent with theoretical predictions which suggest that increased welfare may draw more people into welfare programs while not inducing them to leave (see the models in Ham and Shore-Sheppard (2005); Strumpf (2011)).

These theoretical arguments indicate a negative effect of health insurance on labour supply. Nevertheless, it is important to emphasize that these models are framed in the

context of Medicaid in the US and might not be applicable to low and middle income countries. They seem to ignore the in-kind benefits of health insurance which potentially have a positive health impact on recipients. With better access to healthcare, the poor may become healthier, more productive and hence can work more to increase their income. This health fostering argument combined with a human right based approach is widely used by UCH proponents. Nevertheless, data on health status are normally unavailable in labour market surveys to test this hypothesis (Strumpf, 2011). Additionally, the empirical evidence of the effects of health insurance on health is rather thin especially for adults (Sommers et al., 2012). Whereas, this health-improvement assumption does not always hold true because health insurance is not easily translated into better health (Levy and Meltzer, 2004) as it depends on the generosity of the coverage as well as the infrastructure availability.

The empirical literature on the labour supply effects of health insurance in low and middle income countries is rather limited. According to a recent systematic review (Lê et al., 2017), 47 out of 63 post-2000 publications reviewed are about the US. Similarly, the literature with a particular focus on low income people is mainly concentrated on the US with mixed results (ibid.). Rosen (2014) shows that those without Medicaid tend to work around six hours more per week while an increase in eligibility reduces the employment likelihood by 1.7-7.2 percentage points (Dave et al., 2015). Other studies, however, find insignificant results of Medicaid introduction and expansion on labour supply in terms of work hours (Gooptu et al., 2016) and labour force participation (Strumpf, 2011; Ham and Shore-Sheppard, 2005). This inconclusive result is also confirmed by another synthesis by Gruber and Madrian (2002) who reviewed the US literature published before 2000.

There is no study for Vietnam on the labour supply effects of health insurance for the poor. Recent evaluations of health insurance in Vietnam have instead investigated the effects of health insurance expansion on out-of-pocket spending (Jowett et al., 2003; Wagstaff, 2010; Nguyen, 2012; Nguyen and Wang, 2013), healthcare utilization (Wagstaff, 2007, 2010; Nguyen, 2012; Nguyen and Wang, 2013; Guindon, 2014; Palmer et al., 2015) and health outcome (Guindon, 2014). Two studies specifically assessing HCFP (Wagstaff, 2007, 2010) also fall into this discourse. However, results from these two studies are relatively sensitive to the methodological choices made, which make one question the robustness of the results presented. Wagstaff (2007) used a single difference and Propensity Score Matching to find that HCFP substantially increased service utilization while in another study using triple differences, he concluded that HCFP did not change service utilization albeit reducing out-of-pocket payment (Wagstaff, 2010). Thus, the evidence of the impacts of HCFP on these outcomes is limited and inconclusive, whereas the labour supply effects in particular are under-studied.

3 The Vietnam Health Care Fund For The Poor

The expansion of health coverage in Vietnam has recently accelerated owing to improvements in living standards in fast-growing regions as well as the global push for UHC. After the 1986 Reform, normally referred as 'Doi Moi', wherein the economy was shifted from a centrally planned system to a more open and market-oriented economy, the Vietnamese government has conducted a plethora of healthcare reforms (Wagstaff, 2010) to improve healthcare access and coverage. One illustration is HCFP, which was

introduced in 2003 as a subsidized health scheme for the poor and ethnic minority peoples. The aim was to tackle ever increasing out-of-pocket payment, especially for the poor and vulnerable (Wagstaff, 2010).

HCFP was founded under the Decision 139/2002/QD-TTg, under which provincial governments are mandated to allocate an annual sum for the Provincial Agency of labour - invalids and social affairs - a subordinate body under Ministry of Labour - Invalids and Social affairs- MOLISA- to buy health insurance cards and then have them delivered to the poor within the province. The budget was allocated annually based on a list of poor people proposed by the agency which gathered information from lower level agencies at district and commune levels via hierarchical reporting. The fund was co-financed by both the central and provincial governments and was introduced to replace its the previous programme called Free Health Card (FHC) for the Poor.

According to Decision 139/2002/QD-TTg (Socialist Republic of Vietnam, 2002), HCFP is to target the poor as defined by MOLISA's national poverty line issued under Decision 1143/2000/QD-LDTBXH (Socialist Republic of Vietnam, 2000). However, in reality the specification of poor households at local level was done via community meetings and consultation with local authorities who would then submit an annual list of poor people to provincial authorities. The fund targeted everyone living in the most disadvantaged communes listed under Programme 135 - one of the largest poverty reduction programmes in Vietnam under Decision 135/1998/QD-TTg (Socialist Republic of Vietnam, 1998) - or those belonging to ethnic minority groups who live in the poorest Central Highland and Northern West provinces.

HCFP pays 100 percent of the insurance premium for the poor (around 2.5 USD per person per year in 2003) to ensure that every poor can get free access to any public healthcare facilities affiliated with national social health insurance scheme. The Fund then directly pays to service providers upon utilization (according to Decision 139/2002/QD-TTg). This is to ensure that the poor, by law, do not have to pay out-of-pocket in advance. Even though the regulation requires that provincial authorities buy health insurance for the poor, during the implementation process, provincial governments can chose to i) either buy and issue free health insurance cards for the poor and hence automatically enrol them into national social health insurance scheme or ii) directly reimburse service providers for healthcare services delivered (Tran et al., 2011).

In reality, many provincial governments normally use both approaches: i) issuing health insurance and ii) providing free healthcare services for the poor irrespective of the availability of health insurance cards (Tran et al., 2011). In the latter case, poor certificates, which serve as an identification for the poor, can be used instead when seeking free treatment. Qualitative evidence also shows that some provinces tried to shift the financial burden to the social health insurance system by enrolling sick people into the national insurance scheme while providing user-fee exemption and direct reimbursement to the remaining poor (Tran et al., 2011). Therefore, some policy modifications were made in 2005 to remove direct reimbursement and ensure that the poor have health insurance (ibid.). This crucial right was then embraced in subsequent health regulations (i.e Health Insurance Law versions in 2008 and 2014). However, the flexibility and inconsistency during the early stage of implementation as aforementioned complicates our analysis as we cannot disentangle the effects of health insurance issued under HCFP and its precedent FHC because the health insurance card could be absent if the poor used poor certificates upon healthcare seeking. Therefore, in this analysis, we decide not to separate the two, which is consistent with previous studies like Wagstaff (2010).

4 Data and Methodology

We use panel data from Vietnamese Household Living Standard Surveys (VHLSS) 2002-2006. VHLSS is a nationally representative multi-purpose household survey in Vietnam conducted every two years since 2002 and covers many areas including demographics, expenditure, income, health, labour supply, education and so on. This survey originated from the well-known World Banks Living Standard Measurement Surveys (LSMS) and was renamed VHLSS since 2002. Data collection is currently carried out by Vietnam's General Statistical Office (GSO) with technical support from the World Bank Vietnam. Around 3,000 communes were surveyed every two years, accounting for nearly 30 percent of all communes in Vietnam. Three households per commune were interviewed , making a total household sample size of 9,000. However, because VHLSS uses a sample rotating approach where only half of the sample in a previous survey is re-sampled in the next round, this significantly reduces the sample size of the panel. In other words, a longer panel leads to a smaller sample size. Importantly, during data crunching we find a large number of matching errors in the panel, which is consistent with what is found by McCaig (2009). The author suggested that around 10 percent of matches given by GSO's 2002-2004 official data were imprecise just simply by looking at demographic information such as gender, age and name of the individual (ibid.). The matching errors in VHLSS 2002-2004 panel led to mismatches in the longer panel 2002-2006 that is used in this paper. The poorly matched panel creates biased estimates of many household characteristics (e.g household size, household consumption as illustrated in McCaig (2009)) and influences estimations on many dynamic issues like labour supply, changes in health status and so on (ibid.). Therefore, in this paper, we use the revised household and individual identifiers provided openly on the author's website (McCaig, 2017) to correct for the wrong matches.

After data verification and cleaning, we ended up with a balanced panel which includes 6,808 individuals in each wave. We adopt the universally accepted working age definition and only keep individuals aged between 16 and 65 although labour regulations in Vietnam do not set the upper bound[1]. The age cut-offs reduce the sample size to 4,020, 4,291 and 4,649 individuals respectively. We also remove 338 observations who were covered in 2002 out of FHC scheme before appending the remaining with the later waves to create a balanced panel of 3,564 observations each wave.

One important note about the data is that the survey design in 2002 is relatively simplified compared to the other two waves. Questions on health insurance in the 2002's survey are at the household level while information in 2004 and 2006 is for each household member. We hence assume that if a household is covered with HCFP or FHC in 2002, everyone within the family is covered. This assumption is reasonable given the fact that poverty status in Vietnam is specified at household level via community meetings.

Another data issue is that the 2002 survey merely asked information on HCFP and its precedent FHC while ignoring other health schemes applicable to the working-age poor (namely health insurance for students, health insurance for social assistance recipients and people of merits: the invalid, the handicapped, mothers of war martyrs). Therefore, in our definition of covered and uncovered groups in 2002, we cannot separate the effect of HCFP from other health insurance schemes for the poor (if any). This issue will be discussed further in section 7.

In our definition, *covered* in 2004 and 2006 is defined as being covered by either

[1] According to Vietnam's labour law in 1992 and its amendment in 2004, legal workers are those who are above fifteen.

HCFP or FHC, and not covered by any of other types of health insurance. *Covered* in 2002 is specified as being covered by either HCFP or FHC, and maybe covered by any of other types of health insurance - we simply do not have any information about this. Similarly, *uncovered* refers to not being covered with HCFP nor FHC, but maybe covered by other types of health insurance the poor are eligible for. We then define treatment and control groups. In our data, the baseline year is 2002, before the introduction of HCFP in 2003. Treatment include three sub-groups: i) those covered only in 2006 (group 1), ii) those covered only in 2004 (group 2) and iii) those covered in both years 2004 and 2006. We bundle these three into one treatment group and use group dummies to separate their effects. Those uncovered in all three years form a potential control group for matching.

We combine pre-treatment matching with Difference-in-Differences (DD) to evaluate the effect. Eligibility of health insurance for the poor via HCFP or FHC schemes was not random yet mainly based on poverty status and geographic locations. We therefore use these criteria in our pre-treatment matching to determine a control group before conducting DD estimations.

The matching vector consists of expenditure-based poverty status[2], location (urban or rural), individual and household characteristics that influence the treatment assignment and the outcome equation. These include age, gender, literacy, marital status, relation to the household head, work sector regarding involvement in farming activities, household size, dependency ratio[3], female headed household (dummy). In addition, as local authorities might have prioritized sick and poorer people among the poor in the context of limited budget (Tran et al., 2011), we include healthcare utilization as a proxy for this unobserved health status in the matching vector.

Importantly, due to criticism of and concern about Propensity Score Matching (PSM) methods (see King and Nielsen (2016)), we deliberately choose Mahalanobis matching over the widely used PSM. However, following the advice by King and Nielsen (2016), we also conduct a number of PSM attempts (including Kernel algorithms, and nearest neighbour matching) and then compare matching results regarding efficiency, level of bias reduction before switching to the Mahalanobis metric.

We find that PSM in our case is not an optimal choice due to its inability to completely remove imbalances between the treated and the untreated (see Appendices A9-12 for T-Test results and variance ratios of the matchings). Consequently, PSM attempts result in a very small number of off-support observations even though we know with certainty that treatment selection bias is an issue because health insurance for the poor were not randomly assigned. This is probably due to, what is explained by King and Nielsen (2016), the blindness of PSM to many imbalances as the method tries to approximate a perfect randomization. We also find that Mahalanobis matching in our case is more efficient by fully removing imbalances and bias between the two groups.

The technique, however, comes with a trade-off: after the Mahalanobis matching, we have to remove from the baseline 411 off-support treated observations which are not compatible with any observations in the potential control group. This number of trimmed observations is relatively large in the total number of 665 treated observations in 2002. Based on the TTest results (see Appendices A9-A12) the imbalances mostly come from two household characteristics, i.e the household size and whether the household is headed by a female. These two covariates appear to be important determinants of the treatment

[2] We use poverty line (Glewwe, 2003) in 2002 to identify who were poor in the baseline year 2002

[3] this is defined as the total number of dependants aged below 16 or above 65 over the total household size

assignment in our diagnostic regressions. Therefore, we use Mahalanobis matching as the most stringent method. We, however, also use other matching metrics as robustness checks.

The final sample for DD estimations includes 252 treatment and 2,901 control individuals each wave. We use two dependent variables: i) number of hours worked per month on average as left-censored variable and ii) probability of employment as a binary choice. We respectively employ Tobit and linear probability models for these two outcomes. We employ bootstrap method in estimating standard error and confidence interval for all regressions. The reduced form specifications are as follows:

$$hour_{it} = \alpha treat_i + \beta_k post_k + \delta_k treat_{it} * post_{itk} + \lambda_j treatdummies_j + X'_{it}\gamma + u_{it} \quad (1)$$

$$employ_{it} = \alpha treat_i + \beta_k post_k + \delta_k treat_{it} * post_{itk} + \lambda_j treatdummies_j + X'_{it}\gamma + u_{it} \quad (2)$$

where:

hour denotes number of hours worked per month on average

employ=1 if currently employed and =0 otherwise.

treat=1 for treated individuals, treat=0 for the control.

$post_k$ denote post-treatment dummies with k runs from 1 to 2 that respectively denotes 2004 and 2006

treat dummies include dummies for three different treatment groups, with j running from 1 to 3.

X' is the vector of control variables that explain labour supply. X' also includes the intercept.

u is the error term.

i and t respectively denote individual and time subscripts.

δ_k is the average treatment effect (ATT) of interest in 2004 and 2006 respectively.

Individual and household characteristics in vector X' consist of age, age squared, gender, literacy, marital status, relation to the household head, household size and dependency ratio. Additionally, we proxy for health status by the number of healthcare visit per year. We also account for the effects of labour demand by specifying the geographical regions where the individuals are living using the variable 'urban' and the availability of programme 135, one of the largest and the most important poverty reduction programmes targeting the poorest communes in Vietnam. We control for the farming sector, which is the most common for the Vietnamese rural poor, and type of work (wage-employment in particular). Finally, because the majority of our sample work in farming sector, we try to control for seasonal effects by adding interview month.

5 Results

5.1 Descriptive results

Coverage of HCFP or its precedent during 2002-2006 is presented in table 1. As suggested, coverage increased over time during 2002-2006. Those who were covered in 2002 were the beneficiaries of FHC policy which was then replaced by HCFP in late 2002 and 2003. The

introduction of HCFP indeed has contributed to raising the coverage for eligible people, from nearly 17 percent in 2002 to around 40 and 50 percent in 2004 and 2006 respectively. Inclusion error was another issue as more than 11 per cent of those ineligible in 2006 got coverage. Whereas, exclusion error was high, probably due to budget constraints as in 2006 only half of eligible poor population were covered. Our findings of inclusion and exclusion errors are consistent with other estimates of HCFP coverage and leakage (see Wagstaff (2010)).

Table 1: HCFP and FHC coverage (in percentage)

Whole population									
	2002			**2004**			**2006**		
Eligibility	No	Yes	Total	No	Yes	Total	No	Yes	Total
Uncovered	96.76	83.20	92.22	93.93	64.98	87.47	88.64	50.01	81.70
Covered	3.24	16.80	7.78	6.07	35.02	12.53	11.36	49.99	18.30
Working-age population									
Uncovered	97.04	84.06	93.16	94.14	64.42	88.28	91.48	50.87	84.84
Covered	2.96	15.94	6.84	5.86	35.58	11.72	8.52	49.13	15.16

Eligibility is based on Decision 139/2002/QD-TTg. This coverage is sampling weighted.

Table 2: Descriptive results - matched individuals only

	2002		**2004**		**2006**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Age	36.18	11.83	38.18	11.83	40.18	11.83
Male (dummy)	0.50	0.50	0.50	0.50	0.50	0.50
Literacy (dummy)	0.96	0.19	0.96	0.20	0.96	0.20
Marital status	1.81	0.46	1.83	0.47	1.86	0.46
Household size	4.82	1.57	4.71	1.54	4.57	1.54
Dependency ratio	0.31	0.21	0.29	0.21	0.26	0.21
Number of healthcare utilization per year	0.21	0.50	0.41	0.66	0.48	0.70
Urban (dummy)	0.23	0.42	0.25	0.43	0.25	0.44
Belongs to P135 communes	0.11	0.31	0.09	0.28	0.09	0.28
Currently employed	0.88	0.33	0.89	0.31	0.90	0.30
Sample size		3153		3153		3153
Among employed individuals						
-Number of hours worked per month	160.88	58.32	157.24	63.71	162.03	63.25
-Engaged in wage employment	0.36	0.48	0.41	0.49	0.41	0.49
-Self-employed in agri/aquaculture	0.71	0.45	0.70	0.46	0.66	0.47
-Self-employed in non-farm sector	0.27	0.44	0.28	0.45	0.28	0.45
-Work sector: agri/aquaculture (dummy)	0.59	0.49	0.54	0.50	0.51	0.50
Sample size		2769		2809		2830

SD: Standard errors

Descriptive results of the control variables are shown in Table 2. This descriptive picture is drawn from the truncated panel after matching. In general, the majority of eligible individuals in our final sample are literate (at 96 percent). Additionally, they live in households where dependants make up around one third of total household size which is on average at nearly 5 people per household. Approximately 88-89 percent are

participating in the labour market, the majority of which are self-employed in agri/aquaculture sector (respectively making up 71, 70 and 66 percent of those employed in 2002, 2004 and 2006). This is because more than 75 percent of them are living in rural areas.

Notably, even though the HCFP is designed to target the poor and ethnic minority peoples living in disadvantaged regions of Vietnam, it is important to emphasise that the programme does have spill-over effect to the non-poor who were covered due to inclusion error (See Table 2) or because of the discrepancy in defining poverty in Vietnam. We use World Bank expenditure based poverty line in 2002 while in reality HCFP (or HC) coverage is specified by an official poverty status decided by community meetings. This leads to an unavoidable inclusion error for this study [4]. Thus, the treated in our sample also include the non-poor in all periods - this helps to explains the large number of control individuals kept in all matching methods as well as the larger number of non-poor control individuals who are compatible with the non-poor treated people. Besides, the large number of the non-poor in the treated also reflects the complication in the targeting strategy of the programme which also consists of categorical targeting components (by racial status and geographical location) rather than just the poverty status (means-tested targeting).

Table 3: Treatment assignment by poverty status and eligibility

	Control	Treatment	Total
Non-poor	8,139	605	8,744
Poor	564	151	715
Ineligible	7,555	349	7,904
Eligible	1,148	407	1,555
Total	8,703	756	9,459

5.2 Results

Difference-in-Differences Matching estimates are presented in Table 4 and 5. We initially add individual and household characteristics in model 2 and then expand the model to control for health status (model 3), geographical location (model 4-5) and type of employment, sector (farm or non-farm), and interview month (model 7).

The sign of δ_k - coefficients of the interaction terms between post-treatment dummies (2004 and 2006) and treatment assignment (variable 'treat') changes from positive in 2004 (albeit insignificant) to significantly negative in 2006. This suggests that ATT of health insurance for the poor, if statistically significant, is positive in 2004 but negative in 2006. Both negative and positive effects are simultaneously evidenced as predicted by contradicting theories discussed earlier.

In the short run those who got covered by free health insurance increased their labour supply during 2002-2004. This positive effect dominates and yields a positive net effect (albeit statistically insignificant) on the number of hours worked. However, over time the income effect manifests itself and results in a negative net effect. Notably, the net effect in 2004 is statistically insignificant in all regressions. The effect in 2006 is statistically significant and negative, suggesting the statistical power of the income effect in 2006. On

[4] This also leads to the difference in poverty statistics in Vietnam by the World Bank and MOLISA (Ministry of Labour, the Invalid and Social Affairs). Therefore, poverty reports in Vietnam always report the two groups of statistics together

average, those with free health insurance tend to work around 12.3 to 14.9 hours less per month in 2006 than in 2002.

Table 4: Number of hours worked per month 2002-2006

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
treat	2.395	-2.348	-3.663	-1.500	-0.869	-0.150	5.047
	(6.73)	(5.36)	(5.14)	(5.53)	(6.12)	(6.08)	(7.41)
2004 (dummy)	-1.054	-2.435	-1.127	-1.306	-1.354	-1.566	-4.989**
	(2.55)	(2.00)	(1.83)	(2.27)	(2.39)	(2.11)	(1.97)
treat × 2004	3.794	2.685	3.752	3.903	3.856	3.812	1.235
	(5.95)	(5.62)	(5.43)	(6.27)	(6.38)	(4.99)	(7.03)
2006 (dummy)	5.912***	4.045*	5.731***	5.584***	5.560***	5.166**	1.883
	(2.19)	(2.08)	(2.09)	(2.01)	(1.90)	(2.07)	(2.26)
treat × 2006	-12.331**	-14.194**	-12.937*	-12.718**	-12.941**	-12.911*	-14.876**
	(6.18)	(6.60)	(7.58)	(5.61)	(5.23)	(6.81)	(6.98)

Standard errors in parentheses. This table shows the coefficients of the Tobit regressions. N=9,459

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 presents Difference-in-Differences Matching estimates of the second outcome: the probability of employment. In general, the results seems consistent with the first outcome: HCFP coverage is associated with an increased probability of employment in 2004 albeit linked to a decrease in 2006. However, these effects are not statistically significant in both years 2004 and 2006. This suggests that HCFP coverage in 2004 and 2006 did not significantly affect labour force participation of the Vietnamese poor. These results together with findings in Table 4 suggest that the net impact of HCFP on the target population is positive in the short run yet become negative in the longer run when the income effect kicks in and dominates the health-fostering effect.

Table 5: Probability of employment 2004-2006

	(1)	(2)	(3)	(4)	(5)	(6)
treat	0.066***	0.034*	0.033*	0.018	0.015	0.015
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
2004 (dummy)	0.012**	0.002	0.003	0.004	0.005	0.007
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat× 2004	0.003	0.003	0.004	0.003	0.003	0.003
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
2006 (dummy)	0.021***	0.004	0.005	0.006	0.006	0.008
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat × 2006	-0.017	-0.020	-0.018	-0.020	-0.019	-0.018
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)

Standard errors in parentheses. N=9,459

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Because the employment structure and type of work are significantly different in rural and urban areas, we also break down the results by region. Table 6 suggests that the dominance of the income effect in 2006 is mainly driven by rural individuals (the effect for urban individuals is not statistically significant compared to 10 percent significance level of the effects for rural individuals probably due to the smaller sample of urban people). The HCFP's impact on the probability of employment are statistically insignificant in both years 2004 and 2006 across regions albeit the effect for urban individual is larger in size. This is probably due to the availability of more job opportunities in the urban areas.

Table 6: Number of hours worked per month by region

	(1)	(2)	(3)	(4)	(5)	(6)
For individuals in urban areas (N=2,315)						
treat	11.242	32.716	31.148	31.861	31.823	42.411
	(60.45)	(41.00)	(32.67)	(31.32)	(39.74)	(35.84)
2004 (dummy)	2.152	1.361	2.514	3.110	3.076	4.425
	(5.68)	(4.62)	(5.32)	(4.67)	(5.10)	(6.62)
treat × 2004	17.541	5.504	5.160	4.529	5.040	4.668
	(46.69)	(40.63)	(41.81)	(37.34)	(42.90)	(39.77)
2006 (dummy)	11.175*	10.033*	11.568*	12.146**	12.071**	13.366**
	(6.00)	(5.17)	(6.31)	(4.97)	(5.22)	(6.20)
treat × 2006	-24.059	-39.146	-38.159	-38.797	-38.255	-30.477
	(49.50)	(44.05)	(44.83)	(42.85)	(44.65)	(34.70)
For individuals in rural areas (N=7,144)						
treat	2.356	-2.613	-3.769	-3.050	-2.442	1.429
	(5.96)	(6.30)	(5.37)	(5.13)	(6.32)	(5.12)
2004 (dummy)	-2.434	-3.828	-2.653	-2.694	-2.909	-7.903***
	(2.45)	(2.42)	(2.08)	(2.14)	(2.26)	(2.66)
treat× 2004	4.133	4.088	5.072	5.005	4.968	2.748
	(5.25)	(6.91)	(5.45)	(5.99)	(5.89)	(5.91)
2006 (dummy)	3.861*	1.945	3.449	3.438	3.039	-1.588
	(2.23)	(1.64)	(2.39)	(2.70)	(2.18)	(2.44)
treat × 2006	-9.864*	-10.274*	-9.193*	-9.460*	-9.414	-11.507*
	(5.50)	(5.69)	(5.01)	(5.66)	(6.20)	(6.70)

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Probability of employment by region

	(1)	(2)	(3)	(4)	(5)
For individuals in urban areas (N=2,315)					
treat	-0.087	-0.001	-0.004	-0.023	-0.023
	(0.15)	(0.11)	(0.11)	(0.10)	(0.10)
2004 (year dummy	0.001	-0.005	-0.002	0.023	0.023
	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)
treat × 2004	0.075	0.039	0.038	0.026	0.026
	(0.14)	(0.14)	(0.14)	(0.11)	(0.15)
2006 (year dummy)	0.026	0.018	0.021	0.046**	0.046**
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
treat × 2006	-0.001	-0.053	-0.051	-0.060	-0.060
	(0.16)	(0.15)	(0.17)	(0.13)	(0.16)
For individuals in rural areas (N=7,144)					
treat	0.058***	0.023	0.022	0.022	0.018
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
2004 (year dummy)	0.019*	0.006	0.007	0.002	0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat × 2004	-0.007	-0.003	-0.003	-0.002	-0.002
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
2006 (year dummy)	0.022**	-0.001	0.001	-0.005	-0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat × 2006	-0.018	-0.015	-0.014	-0.014	-0.012
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Because the treated individuals in our sample also include the non-poor while the income effect as well as health improvement effect might be significantly different for individuals of different levels of initial income level, it is hence important to distinguish the effect for the poor and the non-poor to evaluate the effects on the target group of interest. The effect signs of these two groups are consistent with the general trend in Table 4. Interestingly, Table 8 suggests that the statistical significance of the general effects found in Table 4 are mainly driven by the non-poor treated individuals. On average, the treated non-poor are working 13-14 hours less than the non-poor control individuals in 2006 and this effect is significant at 10 percent level. In contrast, the poor albeit working 17- 22 hours less per month in 2006, the effect is statistically insignificant.

Table 8: Number of hours worked by poverty status

	(1)	(2)	(3)	(4)	(5)	(6)
Poor individuals (N=715)						
treat	-8.655	-4.330	-4.423	-4.488	-11.635	-14.123
	(10.66)	(13.13)	(14.77)	(12.70)	(14.30)	(11.40)
2004 (year dummy)	-9.333	-11.599	-10.233	-10.298	-10.711	-25.243***
	(8.51)	(7.57)	(7.65)	(6.57)	(7.24)	(8.45)
treat × 2004	6.537	5.182	8.494	8.881	11.180	14.305
	(10.87)	(13.21)	(12.55)	(12.03)	(12.75)	(11.52)
2006 (year dummy)	-20.480*	-24.228*	-23.609*	-23.786*	-23.375*	-28.921**
	(10.75)	(14.33)	(13.83)	(13.64)	(12.75)	(13.44)
treat × 2006	18.087	17.355	21.767	22.282	22.343	13.420
	(13.99)	(17.06)	(17.43)	(14.36)	(19.82)	(16.57)
Non-poor individuals (N=8,744)						
treat	3.029	-1.758	-3.050	-1.058	0.332	6.206
	(6.73)	(7.37)	(7.15)	(7.35)	(6.89)	(6.33)
2004 (year dummy)	1.222	-0.746	0.493	0.397	0.215	-3.079
	(2.93)	(2.91)	(2.34)	(2.18)	(2.30)	(2.71)
treat × 2004	4.261	4.719	5.468	5.618	5.680	3.976
	(7.53)	(7.24)	(7.16)	(7.99)	(6.91)	(7.05)
2006 (year dummy)	8.621***	5.576**	7.167***	7.175***	6.776***	3.391*
	(2.80)	(2.56)	(2.54)	(2.09)	(2.05)	(1.85)
treat× 2006	-12.988*	-15.309*	-14.318**	-14.830*	-14.438*	-15.355**
	(7.45)	(7.84)	(6.40)	(7.60)	(8.42)	(7.33)

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Probability of employment by poverty status

	(1)	(2)	(3)	(4)	(5)
Poor individuals (N=715)					
treat	0.036**	0.044	0.044	0.047*	0.047
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
2004 (dummy)	-0.029	-0.045*	-0.045	-0.060*	-0.059*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
treat × 2004 (dummy)	0.057	0.052	0.052	0.046	0.048
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)
2006 (dummy)	-0.081*	-0.097**	-0.097	-0.100	-0.100*
	(0.05)	(0.05)	(0.06)	(0.07)	(0.05)
treat× 2006 (dummy)	0.106**	0.108*	0.108*	0.092	0.097*
Non-poor individuals (N=8,744)					
treat	0.070***	0.033	0.031	0.031	0.025
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
2004 (dummy)	0.024***	0.011	0.012	0.021**	0.022*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat × 2004	-0.007	-0.002	-0.002	0.000	-0.000
	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
2006 (dummy)=1	0.034***	0.013*	0.014*	0.022***	0.022*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat × 2006	-0.023	-0.028	-0.027	-0.026	-0.024
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6 Robustness checks

As mentioned, we tried different PSM techniques before switching to Mahalanobis matching. We also ran regressions for the matched samples from these matching techniques, the results are reported below. The results of hours worked are consistent with that of Mahalanobis matching in terms of the effect sign. However, the effect size decreases from a reduction of 12-14 (Mahalanobis) to 8.1-9 hours worked per month (other matching methods). The standard errors are also larger in the latter where the significance level of the coefficients of interest slightly changes from 5 percent to 10 percent. These changes in the effect size and significance level are due to the fact that Mahalanobis

matching removed more treated observations than other matching alternatives. When these treated observations were kept for the latter, it underestimates the effect as the control observations are not perfectly matched (see more details in the Appendix).

However, in general, the general message does not change: we still find a significantly negative effect on the number of hours worked in 2006 and insignificantly positive effect in 2004. The conclusions of the health effect and the income effect hold true and robust across matching techniques used.

Table 10: Number of hours worked per month - PSM methods combined with DD

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Nearest Neighbour Matching, N=10,647							
treat	-2.101	2.205	2.035	1.805	1.236	1.566	3.722
	(4.27)	(3.99)	(3.54)	(4.10)	(4.16)	(3.93)	(3.87)
2004 (year dummy)	-1.059	-2.296	-1.009	-1.128	-1.087	-1.146	-4.054
	(2.28)	(2.09)	(2.04)	(1.87)	(2.13)	(2.17)	(3.20)
treat × 2004	1.306	0.374	0.804	1.037	0.998	1.003	0.336
	(5.43)	(4.21)	(4.63)	(4.52)	(4.56)	(4.16)	(4.50)
2006 (year dummy)	5.903**	4.170	5.835***	5.797***	5.814***	5.705**	2.888
	(2.33)	(2.58)	(2.10)	(1.75)	(2.26)	(2.41)	(2.17)
treat × 2006	-8.511	-9.064*	-8.534*	-8.244	-8.224*	-8.213*	-8.879*
	(6.29)	(5.05)	(4.69)	(5.24)	(4.56)	(4.57)	(4.97)
Kernel matching method (minima maxima algorithm), N= 10,647							
treat	-2.101	2.205	2.035	1.805	1.236	1.566	3.722
	(3.65)	(3.70)	(4.30)	(4.99)	(4.29)	(4.97)	(4.46)
2004 (year dummy)	-1.059	-2.296	-1.009	-1.128	-1.087	-1.146	-4.054
	(2.53)	(2.31)	(2.29)	(2.50)	(2.18)	(2.22)	(2.52)
treat × 2004	1.306	0.374	0.804	1.037	0.998	1.003	0.336
	(4.03)	(4.51)	(4.44)	(4.83)	(5.34)	(5.61)	(4.17)
2006 (year dummy)	5.903**	4.170*	5.835**	5.797**	5.814***	5.705**	2.888
	(2.59)	(2.38)	(2.34)	(2.39)	(2.04)	(2.42)	(2.48)
treat × 2006	-8.511*	-9.064*	-8.534	-8.244**	-8.224*	-8.213	-8.879*
	(4.76)	(5.03)	(5.37)	(4.15)	(4.34)	(5.67)	(4.55)
Kernel matching method (trimming), N =10,653							
treat	-2.083	2.269	2.101	1.872	1.295	1.625	3.766
	(4.67)	(5.06)	(4.04)	(3.58)	(4.75)	(3.61)	(5.28)
2004 (year dummy)	-1.059	-2.300	-1.012	-1.130	-1.089	-1.148	-4.056
	(2.25)	(2.38)	(1.90)	(2.15)	(2.19)	(2.19)	(3.09)
treat × 2004	1.273	0.306	0.719	0.951	0.911	0.916	0.336
	(4.25)	(4.60)	(3.84)	(4.80)	(5.42)	(4.06)	(3.65)
2006 (year dummy)	5.903**	4.163*	5.830***	5.793***	5.810***	5.701***	2.882
	(2.32)	(2.20)	(1.75)	(2.03)	(2.09)	(1.82)	(2.43)
treat × 2006	-8.532*	-9.120**	-8.587**	-8.298*	-8.277*	-8.267*	-8.923**
	(4.68)	(4.36)	(4.26)	(4.66)	(4.29)	(4.45)	(4.35)

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Similarly, we conducted the regressions again using other matching techniques on the probability of working. We found no significant effect of the HCFP on the probability of being employed in both years 2004 and 2006. It is important to emphasise that the

Table 11: Probability of working - PSM methods combined with DD

	(1)	(2)	(3)	(4)	(5)	(6)
Nearest Neighbour Matching, N=10,647						
treat	0.024*	0.042***	0.042***	0.043***	0.038**	0.008
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
2004 (dummy)	0.012	0.004	0.005	0.006	0.007	0.012
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat× 2004	0.001	0.000	0.001	-0.001	-0.002	-0.002
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
2006 (dummy)	0.021**	0.007	0.009	0.009	0.009	0.019**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat × 2006	-0.001	0.000	0.001	-0.001	-0.001	-0.002
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Kernel Matching (maxima minima), N=10,647						
treat	0.024	0.042**	0.042**	0.043**	0.038***	0.008
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
2004 (dummy)	0.012	0.004	0.005	0.006	0.007	0.012*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat × 2004	0.001	0.000	0.001	-0.001	-0.002	-0.002
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
2006 (dummy)	0.021**	0.007	0.009	0.009	0.009	0.019***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat × 2006	-0.001	0.000	0.001	-0.001	-0.001	-0.002
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Kernel Matching (trimming), N=10,653						
treat	0.024*	0.042***	0.042***	0.043***	0.038***	0.008
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
2004 (dummy)	0.012	0.004	0.005	0.006	0.007	0.012
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat × 2004	0.001	-0.000	0.000	-0.001	-0.002	-0.002
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
2006 (dummy)	0.021***	0.007	0.009	0.009	0.009	0.019***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat× 2006	-0.001	0.000	0.001	-0.001	-0.001	-0.002
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Tobit model, which is used to estimate the effect on the number of work hour, is based on the assumption of error normality and homoscedasticity. After Tobit regressions, we conduct a conditional moment test to test the null hypothesis that the disturbances in the Tobit regressions have a normal distribution. This test was developed by Skeels and Vella (1999) who built it on work by Newey (1985) and Tauchen (1985). A rejection of the null hypothesis of error normality suggests that the Tobit estimates are inconsistent. Our diagnostic test unfortunately reveals a rejection of the normality assumption. Therefore,

we followed Cameron and Trivedi (2010) and use two-part and selection models as alternatives for the Tobit. The two-part model consists of two parts, one analysing the determinants of being employed using Probit regressions and the second stage involving OLS regressions on work hours of those employed. This model is used when we assume that the two stages are independent. However, one might suspect that the decision to participate in the labour market (part 1) is not entirely independent of the number of work hour (part 2) because both of these decisions can be determined by individual motivation and many other unobserved characteristics. Therefore, if the assumption of two-part independence does not hold true, we can use the sample selection model and assume that there is some selectivity into the labour market. For identification, we use the non-linear functional form of the selection equation (Cameron and Trivedi, 2010, p.558). The results are presented in the Appendix.

Despite weak consistency caused by non-normality of the error terms in Tobit regressions, the models manage to capture the correct sign and statistical power of the effect of interest because results from the two-part and selection models yield the same conclusion as those of Tobit regressions. The main difference is the effect size on hours worked, respectively at 12.3-14.8 hours in Tobit models, 8.6-10.5 hours in the two-part model and 8.9-10.4 hours in the selection regressions. This means a change in effect magnitude of around 3.7 to 4.4 hours per month. This effect size difference is negligible relative to average monthly work hour which ranges from 157 to 165 hours (see Table 2). Therefore, our conclusion is insensitive to the choice of model despite the failure of Tobit's normality assumption. This probably is thanks to the use of the paired bootstrap method in estimating standard errors which conducts re-sampling based on the sample and hence to some extent minimizes the level of inconsistency caused by non-normal disturbances.

We also investigate the common trend assumption of the DD method. By combing matching with DD, we implicitly assume a parallel trend conditional on the matching covariates. Further diagnosis however is needed to confirm this parallel trend once the matching is done. Unfortunately, we only have one pre-treatment period, making it impossible to test the trend leading to treatment. In our model, we allow time-varying treatment effect, therefore the parallel trend after treatment is relaxed. By adding time-varying covariates in the DD regressions, we can to some extent capture the parallel trend simply by comparing the models with and without these covariates. According to Table 4 and 5, the effect of interest in 2004 and 2006 (the coefficients of the two interaction terms) are relatively similar across Tobit and LPM regressions. This indicates that the common trend assumption after matching holds true.

7 Discussion

We find evidence of two channels through which the HCFP affects labour supply. The health-boosting and income effects found in this paper seem to explain the mixed effects suggested in the literature on health insurance for assistance recipients (see Lê et al. (2017); Gruber and Madrian (2002)) although the income effect seems to be stronger both in sign and magnitude. It is interesting to note that we find evidence to support a health improvement effect in 2004 (albeit insignificant) despite controlling for healthcare utilization in all DD regressions. This somehow indicates that healthcare utilization is not a good proxy for health status given the limited healthcare infrastructure in rural

Vietnam (Cuong, 2010) which potentially hinders poor people from seeking healthcare when needed. This also explains why the health improvement effect in both periods are not strong enough to offset for the work disincentive.

We find that the effects in 2004 and 2006 are mainly driven by the non-poor, especially those living in the rural area. These include non-poor ethnic minority peoples living in disadvantaged areas and hence qualify the categorical targeting criteria. They can also be the near-poor who were not poor based on the World Bank expenditure based poverty line but were defined as poor by the local community. Or they were mistakenly covered due to lots of other implementation complications - this comprises the real inclusion error of the programme. Whereas, in Vietnam the poor in rural regions often comprise ethnic minority individuals living in remote and disadvantaged areas where health access, health literacy are limited (Cuong, 2010) and it often takes some time to raise their awareness of public programmes. Therefore, during the first stage of HCFP wherein direct reimbursement was conducted in many provinces, the programme might not be able to benefit the poorest of the poor probably due to their lower take-up rate and lower healthcare utilization compared to the non-poor who normally live closer to local healthcare centres. Unfortunately, information regarding distance to the nearest healthcare delivery points was not asked in all three data periods so we can not test this hypothesis. Additionally, other studies that looked at utilization and out-of-pocket payment of this specific programme (Wagstaff, 2010, 2007) only examined the average treatment effect for those covered and did not delved deeper into this poverty angle so it is difficult to justify this extrapolation.

Notably, the net effects for the poor in both years are all positive but statistically insignificant, suggesting that the income effect for the poor is dominated by the health improvement effect. However, we will need the effects to be statistically significant to really disprove the argument of welfare dependency discussed earlier by the budget constraint approach.

Most of the existing literature only evaluated the short-term effect - normally right after an intervention. This might not be sufficient as both of these effects normally need some time to materialise. Therefore, in this paper we have taken advantage of the three-wave panel and examined the effects one year and three years after the intervention. We find that the net treatment effect seems to change over time. The effect on hours worked is positive (albeit statistically insignificant) one year after the introduction of HCFP. After three years when the income effect kicks in, it appears to dominate the health improvement effect, yielding a negative net effect on work hours. The change in effect signs is very interesting to discuss. One would expect that for the low income, the income effect will kick in faster than the health impact which is normally take some time to materialise. However, we find the opposite for the rural non-poor people in Vietnam. This may be explained by the very small health premium subsidized as well as the low cost of public healthcare services. Therefore, the income increase relative to the total income of those treated non-poor individuals is not large enough to trigger the income effect from the first year of implementation. Over time, the reduction in out-of-pocket payment (Wagstaff, 2010) could accumulate and materialise to yield a negative and significant net effect. Another explanation is that the theoretical models based on the income effect only investigate the short-term income effect (i.e an income increase due to the subsidy value or reduced health costs) while not examining the income effect in a longer term. If health insurance can improve healthcare access and health, in the long-run people can increase their productivity and then income while working less. This

might be the case for the non-poor individuals where we observe a delay in the income effect.

It is difficult to compare our results with the existing literature due to the over-representation of studies on the US healthcare system as well as the inconclusiveness of the empirical evidence in the US (see the systematic review by Lê et al. (2017)). We have evidence of Medicaid, Childrens Health Insurance Program (CHIP) and Affordable Care Act but the evidence of these studies is rather mixed with different target groups of low-income beneficiaries (ibid.). Our finding of the negative effect on the number of hours worked is conflicting with the majority of the empirical evidence on Medicaid and CHIP. Our estimates regarding the effect on the number of hours worked are smaller in size compared to an effect size of 6 hours per week (or on average 24 hours per month) suggested by Rosen (2014) for Medicaid recipients. This might reflect the larger generosity, and hence bigger income effect, of the Medicaid programme compared to HCFP in Vietnam. Regarding labour force participation, our results are consistent with Strumpf (2011) and Ham and Shore-Sheppard (2005) who suggested that the introduction and expansion of Medicaid did not affect the likelihood of labour force participation. In contrast, these results conflict with Guy et al. (2012) and Dague et al. (2014) who found that low-income childless adults reduced their employment likelihood due to Affordable Care Act. This discrepancy may be explained by the fact that these two studies only focused on childless adults while our paper investigated the working-age population in general. Another reason concerns the discrepancy in the coverage generosity of the Affordable Care Act compared to HCFP in Vietnam.

The finding of a negative net effect of HCFP on the number of hours worked in 2006 for the non-poor raises concern in the context of moving toward UHC in Vietnam. As we find evidence that supports both health boosting and work disincentive effects for the non-poor, the key question for policy makers would be how to better target the poor to avoid unintended labour supply distortions.

This study comes with a data limitation caveat. Effects of other health insurance subsidies other than the HCFP cannot be adequately accounted for due to data limitations in 2002. The health section of 2002's questionnaire does not include any question on health coverage. The information on HCFP and FHC is however asked at the household level in another section on public subsidies and assistance benefits. This is inconsistent with the design of the later surveys in 2004 and 2006 where different types of health insurance are specified for each household member (and hence the level of analysis is at individual level). This data limitation leads us to assume that HCFP is covered for the whole family if a household answered that at least one person within the family receiving this health scheme in 2002. Additionally, due to not being asked, the coverage of other types of health insurance in 2002 is unknown, potentially leading to an under or over estimation of the effect magnitude depending how these health insurances are distributed among treatment and control groups in 2002. However, this data unavailability does not bias our estimates if we assume that conditional on the matching observables, the distribution of other types of health insurance between the treatment and control groups in 2002 are compatible. In this case, the bias caused by other types of health insurance in 2002 would be cancelled out in the pre-treatment difference (in mathematical terms, it equates treatment minus control in the baseline).

8 Conclusion

To conclude, by using Difference-in-Differences Matching methods to evaluate the labour supply effects of free health coverage for the benefit recipients in Vietnam, we examined two outcomes of labour supply: the number of hours worked and employment likelihood. We found that the net effect of free health insurance on work hours was positive albeit statistically insignificant one year after the intervention. However, after three years it became negative and statistically significant. Additionally, we observed the same trend for the probability of employment in the effect sign although the effects did not have statistical significance in both 2004 and 2006. Importantly, the effects were mainly driven by the non-poor people living in rural areas. This raises the question of targeting strategy of the programme, highlights the importance of infrastructure availability as well as awareness raising and improving health literacy for the poor when designing such public health scheme.

We contribute to the existing literature in several ways. First, we help fill the knowledge gap in low and middle income countries where health insurance coverage is rapidly expanding yet not guided by empirical evidence on labour market effects. Second, we analyse the labour supply effects over a longer time span after the intervention. This allows us to capture both health-boosting and income effects induced by health insurance. Third, we dig deeper into the poverty perspective to unravel the mechanisms which are mixed between the two conflicting theoretical predictions.

References

Banerjee, A. V., Hanna, R., Kreindler, G., and Olken, B. A. (2015). Debunking the stereotype of the lazy welfare recipient: Evidence from cash transfer programs worldwide. *Harvard Kennedy School Working Paper No. 076*. Available at SSRN https://ssrn.com/abstract=2703447 or http://dx.doi.org/10.2139/ssrn.2703447.

Boyle, M. A. and Lahey, J. N. (2010). Health insurance and the labor supply decisions of older workers: Evidence from a US Department of Veterans Affairs expansion. *Journal of public economics*, 94(7):467–478.

Cameron, A. C. and Trivedi, P. K. (2010). *Microeconometrics using stata*. Stata Press, College Station, Texas 77845, revised edition.

Chou, S.-Y., Liu, J.-T., and Hammitt, J. K. (2002). Health insurance and households' precautionary behaviors-an unusual natural experiment. *NBER Working Paper No. 9394*. NBER Working Paper No. 9394. Available at http://www.nber.org/papers/w9394.

Chou, Y.-J. and Staiger, D. (2001). Health insurance and female labor supply in Taiwan. *Journal of Health Economics*, 20(2):187–211.

Cuong, N. V. (2010). Public health services and health care utilization in Vietnam. *Munich Personal RePEc Archive 33610*. Available at https://mpra.ub.uni-muenchen.de/33610.

Dague, L., DeLeire, T., and Leininger, L. (2014). The effect of public insurance coverage for childless adults on labor supply. *NBER Working Paper No. 20111*. Avialable at http://www.nber.org/papers/w20111.

Dave, D., Decker, S. L., Kaestner, R., and Simon, K. I. (2015). The effect of Medicaid expansions in the late 1980s and early 1990s on the labor supply of pregnant women. *American Journal of Health Economics*, 1(2):165–193.

Glewwe, P. (2003). Procedure for calculating nominal and real expenditures, and poverty indicators, for the 2002 VHLSS. Available at http://microdata.worldbank.org/index.php/catalog/2306/download/34491.

Gooptu, A., Moriya, A. S., Simon, K. I., and Sommers, B. D. (2016). Medicaid expansion did not result in significant employment changes or job reductions in 2014. *Health affairs*, 35(1):111–118.

Gruber, J. (2010). *Public finance and public policy*. Macmillan, third edition.

Gruber, J. and Madrian, B. C. (2002). Health insurance, labor supply, and job mobility: a critical review of the literature. *NBER Working Paper No. 8817*. Available at http://www.nber.org/papers/w8817.

Guindon, G. E. (2014). The impact of health insurance on health services utilization and health outcomes in Vietnam. *Health Economics, Policy and Law*, 9(04):359–382.

Guy, G. P., Atherly, A., and Adams, E. K. (2012). Public health insurance eligibility and labor force participation of low-income childless adults. *Medical Care research and review*, 69(6):645–662.

Ham, J. C. and Shore-Sheppard, L. D. (2005). Did expanding Medicaid affect welfare participation? *ILR Review*, 58(3):452–470.

Jowett, M., Contoyannis, P., and Vinh, N. D. (2003). The impact of public voluntary health insurance on private health expenditures in Vietnam. *Social Science & Medicine*, 56(2):333–342.

King, G. and Nielsen, R. (2016). Why propensity scores should not be used for matching. Harvard working paper series at http://j.mp/2ovYGsW.

Lagomarsino, G., Garabrant, A., Adyas, A., Muga, R., and Otoo, N. (2012). Moving towards universal health coverage: health insurance reforms in nine developing countries in Africa and Asia. *The Lancet*, 380(9845):933–943.

Lê, N., Groot, W., Tomini, S., and Tomini, F. (2017). Effects of health insurance on labour supply: a systematic review. *UNU MERIT working paper series 2017-017*. Available at http://www.merit.unu.edu/publications/wppdf/2017/wp2017-017.pdf.

Levy, H. and Meltzer, D. (2004). What do we really know about whether health insurance affects health. *Health policy and the uninsured*, pages 179–204.

McCaig, B. (2009). The reliability of matches in the 2002-2004 Vietnam Household Living Standards Survey Panel. *Discussion paper. Centre for Economic Policy Research, Australian National University*. Available at https://www.rse.anu.edu.au/media/604599/dp622.pdf.

McCaig, B. (2017). Note on VHLSS. Data retrieved from Brian McCaig's website, https://sites.google.com/site/briandmccaig/home/notes-on-vhlsss.

Newey, W. K. (1985). Maximum likelihood specification testing and conditional moment tests. *Econometrica: Journal of the Econometric Society*, 53(5):1047–1070.

Nguyen, C. V. (2012). The impact of voluntary health insurance on health care utilization and out-of-pocket payments: New evidence for Vietnam. *Health economics*, 21(8):946–966.

Nguyen, H. and Wang, W. (2013). The effects of free government health insurance among small childrenevidence from the free care for children under six policy in Vietnam. *The International journal of health planning and management*, 28(1):3–15.

Palmer, M., Mitra, S., Mont, D., and Groce, N. (2015). The impact of health insurance for children under age 6 in Vietnam: a regression discontinuity approach. *Social Science & Medicine*, 145:217–226.

Rodin, J. and de Ferranti, D. (2012). Universal health coverage: the third global health transition? *The Lancet*, 380(9845):861.

Rosen, G. (2014). Determinants of employment: Impact of medicaid and CHIP among unmarried female heads of household with young children. *Social work in public health*, 29(5):491–502.

Skeels, C. L. and Vella, F. (1999). A Monte Carlo investigation of the sampling behavior of conditional moment tests in Tobit and Probit models. *Journal of Econometrics*, 92(2):275–294.

Socialist Republic of Vietnam (1998). Decision 135/1998/QD-TTg on socio-economic development plan for the most difficulty communes in mountainous areas and isolated regions. *Prime Minister of Vietnam*.

Socialist Republic of Vietnam (2000). Decision 1143/2000/QD-LDTBXH on poverty line during 2001-2005. *Ministry of Labour, the Invalids and Social Affairs of Vietnam*.

Socialist Republic of Vietnam (2002). Decision 139/2002/qd-ttg on healthcare for the poor. *Prime Minister of Vietnam*.

Socialist Republic of Vietnam (2016). Decision 1167/Q-TTg on target adjustments for expanding health insurance coverage in Vietnam during 2016-2020. *Prime Minister of Vietnam*.

Sommers, B. D., Baicker, K., and Epstein, A. M. (2012). Mortality and access to care among adults after state Medicaid expansions. *New England Journal of Medicine*, 367(11):1025–1034.

Strumpf, E. (2011). Medicaid's effect on single women's labor supply: Evidence from the introduction of Medicaid. *Journal of Health Economics*, 30(3):531–548.

Tauchen, G. (1985). Diagnostic testing and evaluation of maximum likelihood models. *Journal of econometrics*, 30(1-2):415–443.

Tran, V. T., Hoang, T. P., Mathauer, I., and Nguyen, T. (2011). Health financing review of Vietnam with a focus on social health insurance: Bottlenecks in institutional design and organizational practice of health financing and options to accelerate progress towards universal coverage. *World Health Organisation report series*. Available at http://www.who.int/health$_f$*inancing/documents/oasis*$_{f1}$1 − *vietnam.pdf*.

Wagstaff, A. (2007). Health insurance for the poor: initial impacts of Vietnam's health care fund for the poor. *World Bank Policy Research Working Paper No. 4134*. Available at https://ssrn.com/abstract=961760.

Wagstaff, A. (2010). Estimating health insurance impacts under unobserved heterogeneity: the case of Vietnam's health care fund for the poor. *Health economics*, 19(2):189–208.

Wagstaff, A. and Moreno-Serra, R. (2009). Europe and central Asia's great post-communist social health insurance experiment: Aggregate impacts on health sector outcomes. *Journal of health economics*, 28(2):322–340.

Wagstaff, A. and Moreno-Serra, R. (2015). *Social health insurance and labor market outcomes: Evidence from Central and Eastern Europe, and Central Asia*, pages 83–106. Emerald Insight. Available at http://www.emeraldinsight.com/doi/abs/10.1108/S0731-2199

Table A1: Number of hours worked per month 2002-2006 : Tobit regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
treat	2.395	-2.348	-3.663	-1.500	-0.869	-0.150	5.047
	(6.73)	(5.36)	(5.14)	(5.53)	(6.12)	(6.08)	(7.41)
2004 (year dummy)	-1.054	-2.435	-1.127	-1.306	-1.354	-1.566	-4.989**
	(2.55)	(2.00)	(1.83)	(2.27)	(2.39)	(2.11)	(1.97)
treat × 2004	3.794	2.685	3.752	3.903	3.856	3.812	1.235
	(5.95)	(5.62)	(5.43)	(6.27)	(6.38)	(4.99)	(7.03)
2006 (year dummy)	5.912***	4.045*	5.731***	5.584***	5.560***	5.166**	1.883
	(2.19)	(2.08)	(2.09)	(2.01)	(1.90)	(2.07)	(2.26)
treat × 2006	-12.331**	-14.194**	-12.937*	-12.718**	-12.941**	-12.911*	-14.876**
	(6.18)	(6.60)	(7.58)	(5.61)	(5.23)	(6.81)	(6.98)
Age squared		-0.195***	-0.194***	-0.191***	-0.191***	-0.191***	-0.167***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age		15.380***	15.273***	15.065***	15.055***	15.033***	13.387***
		(0.52)	(0.64)	(0.66)	(0.69)	(0.64)	(0.56)
Male (dummy)		15.811***	15.037***	15.398***	15.435***	15.323***	6.045***
		(1.39)	(1.70)	(1.61)	(1.70)	(1.59)	(1.49)
Household size		1.015*	0.847*	0.920	0.948*	0.995*	1.608***
		(0.59)	(0.48)	(0.61)	(0.55)	(0.54)	(0.54)
Dependency ratio		-7.098*	-6.769	-4.295	-4.143	-3.796	-4.725
		(4.27)	(4.31)	(3.67)	(4.89)	(4.85)	(4.18)
Literacy (dummy)		12.318***	11.987**	10.651**	10.117**	9.734*	11.696***
		(4.00)	(4.68)	(4.60)	(4.99)	(5.01)	(4.07)
Marital status (base: married)							
-Never married		-17.097***	-17.844***	-19.304***	-19.391***	-20.462***	-20.644***
		(3.25)	(3.94)	(3.52)	(3.84)	(3.30)	(2.77)
-Widowed/Divorced/Separated		-11.798***	-11.225***	-11.825***	-11.907***	-12.089***	-11.190**
		(4.06)	(3.69)	(4.16)	(4.35)	(4.23)	(4.68)
Number of healthcare utilization p.a			-7.304***	-7.031***	-7.037***	-7.098***	-7.398***
			(1.49)	(1.50)	(1.33)	(1.46)	(1.26)
Urban (dummy)				12.211***	11.973***	9.272***	7.496***
				(2.22)	(2.32)	(2.44)	(2.24)
Work sector: agriculture and aquaculture (dummy)						-6.777***	1.145
						(1.80)	(1.87)
Engaged in wage employment							41.714***
							(1.55)
Constant	136.407***	-151.737***	-147.807***	-146.971***	-145.883***	-140.717***	-126.776***
	(1.80)	(12.14)	(13.88)	(14.94)	(15.64)	(15.42)	(12.25)
N	9,459	9,459	9,459	9,459	9,459	9,459	9,459

Standard errors in parentheses. This table shows the coefficients of the Tobit regressions
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dummies for treatment groups, 'belongs to Programme 135' are included but insignificant
Interview month is included in model (7). Labour supply of those interviewed in February is 35 hours less relative to January

Table A2: Probability of employment 2004-2006: Linear Probability Model

	(1)	(2)	(3)	(4)	(5)	(6)
treat	0.066***	0.034*	0.033*	0.018	0.015	0.015
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
2004 (year dummy)	0.012**	0.002	0.003	0.004	0.005	0.007
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat× 2004	0.003	0.003	0.004	0.003	0.003	0.003
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
2006 (year dummy)	0.021***	0.004	0.005	0.006	0.006	0.008
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
treat × 2006	-0.017	-0.020	-0.018	-0.020	-0.019	-0.018
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Age squared		-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age		0.054***	0.054***	0.056***	0.056***	0.056***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male (dummy)		0.059***	0.059***	0.056***	0.056***	0.056***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size		-0.000	-0.001	-0.001	-0.001	-0.001
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Dependency ratio		0.010	0.010	-0.007	-0.008	-0.007
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Literacy (dummy)		0.041**	0.041**	0.050***	0.053***	0.053***
		(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Marital status (base: married people)						
-Never married		-0.115***	-0.116***	-0.106***	-0.105***	-0.106***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
-Widowed/Divorced/Separated		-0.056***	-0.055***	-0.051***	-0.050***	-0.050***
		(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Number of healthcare utilization per year			-0.007*	-0.009*	-0.009*	-0.009**
			(0.00)	(0.01)	(0.00)	(0.00)
Urban (dummy)				-0.085***	-0.084***	-0.084***
				(0.01)	(0.01)	(0.01)
Constant	0.872***	-0.162***	-0.159***	-0.160***	-0.164***	-0.146**
	(0.01)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)
N	9,459	9,459	9,459	9,459	9,459	9,459

Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Treatment group dummies, 'belongs to Programme 135' are included in but not significant
Interview month is included in (6), suggesting that those interviewed in Apr are 13.2 pp more likely to be employed relative to January

Table A3: Two part model- Part 1: Determinants of being employed 2002-2006 - Probit

	(1)	(2)	(3)	(4)	(5)	(6)
Employed=1: currently employed						
treat	0.390**	0.298	0.285	0.183	0.155	0.156
	(0.18)	(0.29)	(0.25)	(0.30)	(0.28)	(0.25)
2004 (year dummy)	0.061	-0.037	-0.026	-0.020	-0.018	-0.026
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)
treat × 2004 (year dummy)	0.112	0.202	0.214	0.212	0.216	0.221
	(0.19)	(0.24)	(0.26)	(0.26)	(0.27)	(0.27)
2006 (year dummy)	0.105***	-0.038	-0.023	-0.021	-0.021	-0.030
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)
treat × 2006	-0.062	-0.111	-0.097	-0.108	-0.100	-0.097
	(0.20)	(0.27)	(0.24)	(0.28)	(0.26)	(0.24)
Age squared		-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age		0.264***	0.263***	0.279***	0.279***	0.281***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Male (dummy)		0.476***	0.472***	0.453***	0.451***	0.450***
		(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
Household size		-0.005	-0.007	-0.010	-0.011	-0.011
		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Dependence ratio		0.301**	0.302***	0.141	0.129	0.137
		(0.12)	(0.10)	(0.12)	(0.09)	(0.11)
Literacy (dummy)		0.249***	0.246***	0.331***	0.348***	0.345***
		(0.09)	(0.09)	(0.11)	(0.09)	(0.08)
Marital status (base: married)						
-Never married		-0.556***	-0.565***	-0.518***	-0.514***	-0.512***
		(0.08)	(0.07)	(0.06)	(0.06)	(0.07)
-Widowed/Divorced/Separated		-0.301***	-0.293***	-0.273***	-0.269**	-0.264**
		(0.09)	(0.08)	(0.09)	(0.11)	(0.12)
Number of healthcare utilization per year			-0.068**	-0.082***	-0.082**	-0.083***
			(0.03)	(0.03)	(0.03)	(0.03)
Urban (dummy)				-0.529***	-0.519***	-0.516***
				(0.04)	(0.04)	(0.04)
Belongs to P135 communes					0.140*	0.148*
					(0.08)	(0.08)
Constant	1.136***	-3.643***	-3.605***	-3.706***	-3.758***	-3.733***
	(0.03)	(0.31)	(0.26)	(0.33)	(0.28)	(0.33)
N	9,459	9,459	9,459	9,459	9,459	9,457

Standard errors in parentheses. This table shows the coefficients of the Tobit regressions
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dummies for treatment groups are included but insignificant
This table reports the coefficients, not the marginal effects
Interview month is included in model (7) suggests that those interviewed in February are less likely to work

Table A4: Two part models - Part 2: Number of hours worked per month 2002-2006 for those employed - OLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of hours worked per month							
treat	-11.418**	-9.173*	-10.352*	-4.637	-3.399	-3.431	0.628
	(4.93)	(5.21)	(5.53)	(5.15)	(5.53)	(4.38)	(4.98)
2004 (year dummy)	-3.951**	-3.256	-2.019	-2.446	-2.537	-5.671**	-6.302***
	(1.82)	(2.01)	(1.76)	(1.74)	(1.56)	(2.30)	(2.14)
treat × 2004	3.699	2.823	3.763	4.047	3.919	3.573	3.435
	(5.86)	(5.31)	(5.94)	(5.19)	(4.85)	(4.34)	(5.53)
2006 (year dummy)	1.936	3.383**	4.919***	4.400***	4.349***	1.846	-0.223
	(1.73)	(1.63)	(1.28)	(1.68)	(1.44)	(1.95)	(1.88)
treat × 2006	-9.420*	-10.450**	-9.273	-8.565*	-9.015**	-9.388**	-8.618*
	(5.26)	(5.14)	(6.09)	(4.86)	(4.57)	(4.25)	(5.07)
Age squared		-0.074***	-0.072***	-0.062***	-0.062***	-0.062***	-0.045***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age		5.272***	5.185***	4.338***	4.320***	4.294***	3.085***
		(0.46)	(0.51)	(0.44)	(0.49)	(0.48)	(0.53)
Male (dummy)		4.729***	4.009***	4.549***	4.608***	4.664***	3.043**
		(1.41)	(1.54)	(1.15)	(1.14)	(1.20)	(1.45)
Household size		1.179***	1.025**	1.083***	1.141**	1.085***	1.526***
		(0.41)	(0.40)	(0.38)	(0.49)	(0.39)	(0.43)
Dependence ratio		-11.684***	-11.297***	-5.063	-4.794	-5.016	-1.642
		(3.69)	(3.71)	(4.01)	(3.27)	(3.55)	(3.54)
Literacy (dummy)		4.665	4.442	1.042	-0.059	-0.217	-4.254
		(3.59)	(4.07)	(4.14)	(3.57)	(3.13)	(3.54)
Marital status (base: married)							
-Never married		7.137***	6.533**	2.886	2.726	2.465	-3.245
		(2.63)	(2.62)	(2.51)	(2.03)	(2.68)	(2.96)
-Widowed/Divorced/Separated		-3.030	-2.544	-4.063	-4.203	-4.488	-4.141
		(4.30)	(4.01)	(2.54)	(3.16)	(3.98)	(3.01)
Number of healthcare utilization per year			-6.639***	-5.841***	-5.860***	-5.886***	-6.158***
			(1.03)	(1.00)	(0.97)	(1.00)	(1.14)
Urban (dummy)				33.068***	32.611***	32.237***	13.948***
				(1.38)	(1.68)	(1.71)	(1.77)
Belongs to P135 communes					-5.727**	-5.998**	-1.187
					(2.28)	(2.45)	(1.95)
Engaged in wage employment							-1.251
							(1.24)
Work sector: agriculture and aquaculture (dummy)							-44.578***
							(1.51)
Constant	161.732***	67.094***	70.309***	79.034***	81.169***	84.215***	143.455***
	(1.21)	(10.88)	(10.42)	(9.84)	(10.97)	(11.01)	(13.14)
N	8,408	8,408	8,408	8,408	8,408	8,408	8,408

Standard errors in parentheses. This table shows the coefficients of the Tobit regressions
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Dummies for treatment groups are included but insignificant
Interview month is included in model (7). Labour supply of those interviewed in May is 11 hours less relative to that of January

Table A5: Selection models - Outcome equation

	(1)	(2)	(3)	(4)	(5)	(6)
Number of hours worked per month						
Treat	-11.039*	-9.243*	-10.429**	-4.730	-3.480	-3.515
	(5.77)	(5.00)	(4.48)	(5.48)	(5.70)	(3.89)
2004 (year dummy)	-3.094**	-3.249*	-2.015	-2.443	-2.535	-5.688**
	(1.57)	(1.89)	(2.08)	(2.30)	(1.96)	(2.32)
Treat× 2004	3.930	2.792	3.723	3.959	3.829	3.482
	(5.19)	(5.24)	(4.75)	(5.43)	(4.75)	(4.69)
2006 (year dummy)	3.893**	3.388**	4.919***	4.400**	4.350**	1.829
	(1.55)	(1.43)	(1.43)	(1.87)	(1.84)	(2.09)
Treat × 2006	-8.617	-10.423**	-9.244*	-8.498*	-8.950*	-9.322
	(5.35)	(4.73)	(4.78)	(5.03)	(5.17)	(5.83)
Group 1: covered in 2006 only	-4.737	-4.077	-3.663	-4.391	-4.504	-4.211
	(6.30)	(5.62)	(5.46)	(5.67)	(6.03)	(4.94)
Group 3: covered in both years 2004 and 2006	1.560	1.205	1.878	1.881	3.656	4.432
	(7.09)	(6.25)	(4.73)	(4.50)	(5.79)	(5.34)
Age squared	-0.009***	-0.072***	-0.070***	-0.058***	-0.058***	-0.057***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age		5.154***	5.049***	4.015***	3.984***	3.951***
		(0.61)	(0.54)	(0.44)	(0.49)	(0.54)
Male (dummy)		4.591***	3.851***	4.196***	4.243***	4.291***
		(1.48)	(1.43)	(1.39)	(1.41)	(1.11)
Household size		1.181**	1.028**	1.099***	1.158**	1.102**
		(0.49)	(0.50)	(0.41)	(0.47)	(0.47)
Dependence ratio		-11.724***	-11.343**	-5.080	-4.807	-5.030
		(3.15)	(4.41)	(3.59)	(3.17)	(3.74)
Literacy (dummy)		4.574	4.339	0.746	-0.378	-0.544
		(3.70)	(3.44)	(3.43)	(3.47)	(2.84)
Marital status (base: married)						
-Never married		7.414**	6.857**	3.592	3.456	3.211
		(2.88)	(2.86)	(2.24)	(2.73)	(3.03)
-Widowed/Divorced/Separated		-2.916	-2.413	-3.773	-3.906	-4.184
		(3.52)	(3.48)	(4.02)	(3.80)	(3.40)
Number of healthcare utilization per year			-6.617***	-5.777***	-5.793***	-5.818***
			(1.12)	(1.21)	(1.25)	(0.96)
Urban (dummy)				33.549***	33.103***	32.740***
				(1.52)	(1.76)	(1.66)
Belongs to P135 communes					-5.815**	-6.089**
					(2.34)	(2.36)
Constant	178.295***	69.636***	73.240***	85.832***	88.250***	91.400***
	(7.45)	(14.04)	(12.72)	(9.51)	(12.09)	(12.46)

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Interview month is included in model (6)

Table A6: Selection models - Selection equation

	(1)	(2)	(3)	(4)	(5)	(6)
Currently employed (dummy)						
treat=1	0.364	0.297	0.283	0.179	0.150	0.150
	(0.24)	(0.27)	(0.25)	(0.30)	(0.28)	(0.28)
2004 (year dummy)	0.017	-0.037	-0.026	-0.019	-0.017	-0.016
	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)
treat × 2004	0.134	0.201	0.213	0.211	0.215	0.215
	(0.22)	(0.31)	(0.28)	(0.26)	(0.30)	(0.31)
2006 (year dummy)	0.014	-0.037	-0.022	-0.018	-0.017	-0.017
	(0.04)	(0.06)	(0.06)	(0.04)	(0.05)	(0.06)
treat× 2006	-0.035	-0.109	-0.094	-0.102	-0.093	-0.093
	(0.23)	(0.27)	(0.27)	(0.27)	(0.28)	(0.22)
Group 1: covered in 2006 only	0.212	0.012	0.016	0.081	0.098	0.098
	(0.25)	(0.27)	(0.25)	(0.32)	(0.28)	(0.31)
Group 3: covered in both years 2004 and 2006	0.149	-0.098	-0.092	-0.082	-0.122	-0.122
	(0.26)	(0.33)	(0.27)	(0.31)	(0.25)	(0.25)
Age squared	0.000***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age		0.264***	0.263***	0.279***	0.280***	0.280***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Male (dummy)		0.475***	0.471***	0.450***	0.448***	0.448***
		(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
Household size		-0.005	-0.007	-0.010	-0.011	-0.011
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Dependence ratio		0.300***	0.301***	0.139	0.127	0.127
		(0.11)	(0.11)	(0.12)	(0.12)	(0.10)
Literacy (dummy)		0.248***	0.244**	0.327***	0.344***	0.344***
		(0.09)	(0.10)	(0.11)	(0.11)	(0.08)
Marital status (base: married)						
-Never married		-0.555***	-0.564***	-0.515***	-0.511***	-0.511***
		(0.07)	(0.07)	(0.06)	(0.06)	(0.07)
-Widowed/Divorced/Separated		-0.302***	-0.294***	-0.273***	-0.270***	-0.269***
		(0.09)	(0.11)	(0.08)	(0.08)	(0.08)
Number of healthcare utilization per year			-0.068**	-0.082**	-0.082***	-0.082**
			(0.03)	(0.03)	(0.03)	(0.03)
Urban (dummy)				-0.532***	-0.522***	-0.522***
				(0.05)	(0.04)	(0.05)
Belongs to P135 communes					0.143*	0.143*
					(0.09)	(0.08)
Constant	0.806***	-3.644***	-3.605***	-3.709***	-3.762***	-3.763***
	(0.04)	(0.25)	(0.28)	(0.26)	(0.32)	(0.24)
Athrho constant	-0.148	-0.025	-0.029	-0.072**	-0.075*	-0.076**
	(0.36)	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)
Lnsigma constant	4.118***	4.106***	4.104***	4.078***	4.078***	4.077***
	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	9,459	9,459	9,459	9,459	9,459	9,459

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Descriptive information after Mahalanobis matching

	Mean On support	SD On support	Mean Off support	SD Off support
Age	36.18	11.83	35.81	13.33
Male (dummy)	0.50	0.50	0.45	0.50
Literacy (dummy)	0.96	0.19	0.82	0.38
Marital status	1.81	0.46	1.80	0.57
Household size	4.82	1.57	6.10	2.80
Dependency ratio	0.31	0.21	0.38	0.21
Number of healthcare utilization per year	0.21	0.50	0.27	0.54
Urban (dummy)	0.23	0.42	0.20	0.40
Belongs to P135 communes	0.11	0.31	0.37	0.48
Currently employed (dummy)	0.88	0.33	0.87	0.34
Among those currently employed				
Engaged in wage employment	0.31	0.46	0.26	0.44
Self-employed in agri/aquaculture	0.63	0.48	0.73	0.45
Self-employed in non-farm sector	0.23	0.42	0.18	0.39
Work sector: agriculture and aquaculture (dummy)	0.52	0.50	0.70	0.46

SD: Standard errors

Table A8: Matching results

Sample	Mean Bias	Median Bias	Variance Ratio
Mahalanobis matching			
Unmatched	22.7	16.6	33
Matched	**0.0**	**0.0**	**0**
Number of off-support observations			411
PSM-Kernel algorithm, minima-maxima common support			
Unmatched	22.7	16.6	33
Matched	1.4	1.3	33
Number of off-support observations			15
PSM - Kernel algorithm, trimming at 2 percent for common support			
Unmatched	22.7	16.6	33
Matched	1.4	1.3	33
Number of off-support observations			13
PSM - Nearest neighbour matching algorithm			
Unmatched	22.7	16.6	33
Matched	1.5	1.2	33
Number of off-support observations			15

As illustrated, Mahalanobis matching in this case manage to fully remove bias between the treated and untreated observations (see the results in bold). In contrast, PSM methods fail to fully clean up the imbalances between the two groups and suggest a very small number of off-support observations. This leads us to suspect the quality of PSM metrics which try to approximate a completely randomized sample and potentially ignore many imbalances. Similarly, figures of disturbance variance after matching suggest the use of Mahalanobis matching.

Table A9: TTest results - Mahalanobis Matching

Variable	Mean		TTest		
	Treated	Control	T statistic	P value	Variance ratio
Age	35.21	35.214	-0.00	0.996	1.00
Male	.53968	.53968	0.00	1.000	1.00
Household size	4.6111	4.6111	0.00	1.000	1.0
Dependency ratio	.402	.402	-0.00	1.000	1.00
Literacy	.99206	.99206	-0.00	1.000	1.00
Marital status	1.9127	1.9127	-0.00	1.000	1.00
Female-headed HH	.02381	.02381	-0.00	1.000	1.00
Relation the the HH head	1.6349	1.6349	0.00	1.000	1.00
Urban	.05952	.05952	0.00	1.000	1.00
Poverty status	.29762	.29762	0.00	1.000	1.00
Healthcare utilization	.09127	.09127	-0.00	1.000	1.00
Work sector (agri/aquaculture)	.77778	.77778	0.00	1.000	1.00

* denotes 'of concern', i.e. variance ratio in [0.5, 0.8) or (1.25, 2]

Variance ratio is bad if below 0.5 or above 2

Table A10: TTest results - Nearest Neighbour Matching

Variable	Mean		TTest		
	Treated	Control	T statistic	P value	Variance ratio
Age	35.679	35.626	0.08	0.936	1.10
Male	35.679	35.626	-0.24	0.814	0.95
Household size	5.3549	5.3403	0.14	0.892	1.25*
Dependency ratio	.3819	.38427	-0.21	0.835	0.98
Literacy	.90432	.91397	-0.60	0.546	1.03
Marital status	1.8441	1.8414	0.10	0.918	1.22
Female-headed HH	.06636	.05826	0.60	0.547	1.29*
Relation the the HH head	1.9259	1.9282	-0.05	0.961	1.06
Urban	.15123	.1439	-5.42	0.000	1.05
Poverty status	.4321	.4375	-0.20	0.845	1.02
Healthcare utilization	.19444	.18133	0.53	0.599	1.13
Work sector (agri/aquaculture)	.72377	.72608	-0.09	0.926	1.01

* denotes 'of concern', i.e. variance ratio in [0.5, 0.8) or (1.25, 2]

Variance ratio is bad if below 0.5 or above 2

Table A11: TTest results - Kernel Matching (minima maxima algorithm

Variable	Mean		TTest		
	Treated	Control	T statistic	P value	Variance ratio
Age	35.679	35.987	-0.47	0.638	1.12
Male	.49074	.49223	-0.05	0.957	0.99
Household size	5.3549	5.3399	0.14	0.888	1.34*
Dependency ratio	.3819	.3786	0.29	0.770	0.94
Literacy	.90432	.91168	-0.46	0.647	1.13
Marital status	1.8441	1.8436	0.02	0.984	1.23
Female-headed HH	.06636	.06066	0.42	0.675	1.07
Relation the the HH head	1.9259	1.9228	0.07	0.947	1.09
Urban	.15123	.15863	-0.37	0.713	0.95
Poverty status	.4321	.43245	-0.01	0.990	1.00
Healthcare utilization	.19444	.19967	-0.20	0.841	0.97
Work sector (agri/aquaculture)	.72377	.70734	0.66	0.513	0.89

* denotes 'of concern', i.e. variance ratio in [0.5, 0.8) or (1.25, 2]

Variance ratio is bad if below 0.5 or above 2

Table A12: TTest results - Kernel Matching (trimming at 2 percent

Variable	Mean		TTest		
	Treated	Control	T statistic	P value	Variance ratio
Age	35.68	35.992	-0.48	0.632	1.12
Male	.49077	.4919	-0.04	0.968	0.99
Household size	5.3708	5.349	0.20	0.839	1.35*
Dependency ratio	.38233	.37927	0.27	0.786	0.94
Literacy	.90154	.90888	-0.45	0.652	1.11
Marital status	1.8431	1.8439	-0.03	0.975	1.24
Female-headed HH	.06615	.06061	0.41	0.682	1.08
Relation the the HH head	1.9277	1.9244	0.07	0.944	1.09
Urban	.15077	.15827	-0.37	0.708	0.96
Poverty status	.43385	.43419	-0.01	0.990	1.00
Healthcare utilization	.19538	.19959	-0.16	0.872	0.97
Work sector (agri/aquaculture)	.72462	.70811	0.66	0.509	0.89

* denotes 'of concern', i.e. variance ratio in [0.5, 0.8) or (1.25, 2]

Variance ratio is bad if below 0.5 or above 2

Figure A: Variance ratio of disturbance after matching methods

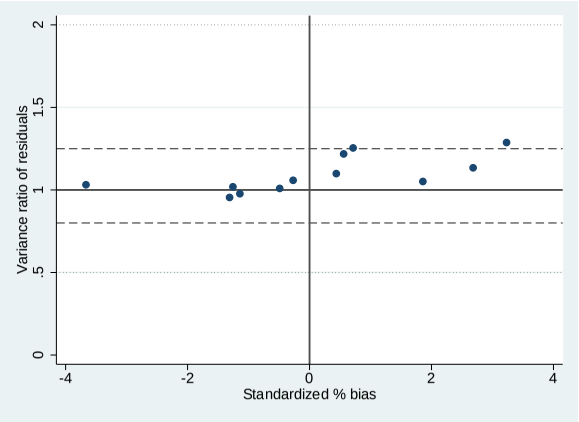

Figure A1: Nearest Neighbour Matching

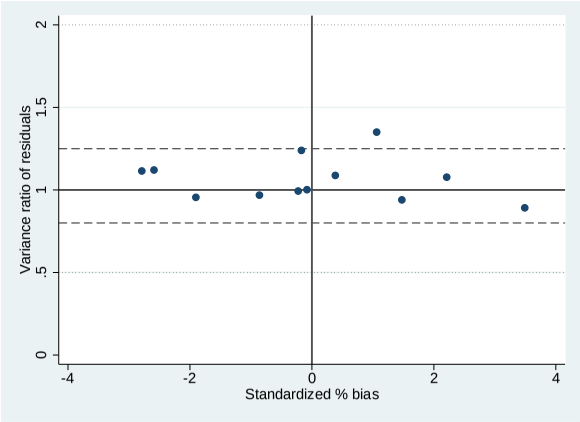

Figure A2: Kernel matching-trimming at 2 percent

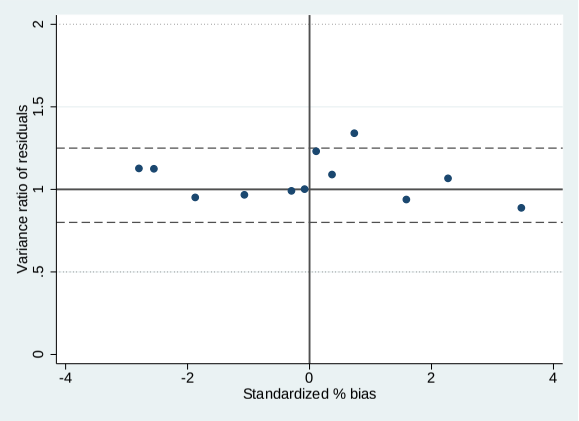

Figure A3: Kernel matching-minima maxima method

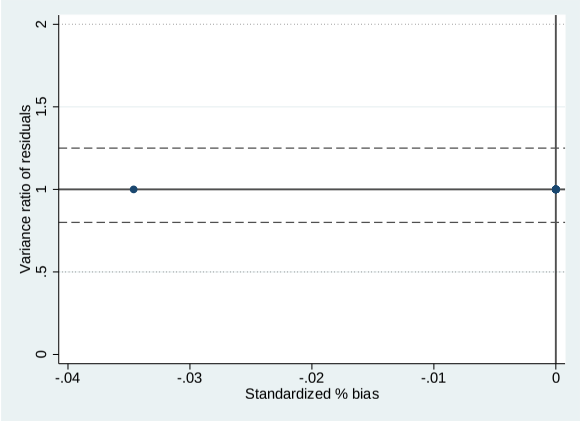

Figure A4: Mahalanobis matching

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