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Corresponding Author: Dr. Shehzad Ali,

Corresponding Author's Institution: University of York

First Author: Shehzad Ali

Order of Authors: Shehzad Ali; Richard Cookson, PhD; Mark  Dusheiko, PhD

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Abstract: Health Insurance (HI) programmes in low-income countries aim to reduce the burden of individual out-of-pocket (OOP) health care expenditure. However, if the decisions to purchase insurance and to seek care when ill are correlated with the expected healthcare expenditure, the use of naïve models may produce biased estimates of the impact of insurance membership on OOP expenditure. Whilst many studies in the literature have accounted for the endogeneity of the insurance decision, the potential selection bias due to the care-seeking decision has not been taken into account. We extend the Heckman selection model to account simultaneously for both care-seeking and insurance-seeking selection biases in the healthcare expenditure regression model. The proposed model is illustrated in the context of a Vietnamese HI programme and results compared with those of alternative models making no or partial allowance for selection bias.  In this illustrative example, the impact of insurance membership on reducing OOP expenditures was underestimated by 21 percentage points when selection biases were not taken into account. We believe this is an important methodological contribution that will be relevant to future empirical work.

**Cover Page**

Shehzad Ali – Research Fellow
University of York
Heslington
York, YO10 5DD, UK
Tel: + 44 (0)1904 321361
Fax: +44 (0)1904 321402
shehzad.ali@york.ac.uk

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Editor-in-Chief, *Social Science and Medicine*

Dear Professor Coast:

On behalf of my co-authors, I would like to submit our response to reviewers' comments and the revised version of our manuscript titled **"Addressing care-seeking as well as insurance-seeking selection biases in estimating the impact of health insurance on out-of-pocket expenditure"** for consideration in *Social Science and Medicine.*

In the attached documents, we have addressed reviewers' comments in detail. As suggested by the reviewers, we have motivated the paper by going through the methods used in the literature to address selection into insurance and care-seeking, with particular attention to studies that addressed both observable and unobservable factors. We have also clarified the need to account for the care-seeking selection bias by elaborating on intensive and extensive margins, and generalisability of the impact of health insurance to the population (and not just those who sought health care).

Also, we have discussed the context of randomised and non-randomised studies of health insurance, particularly in the context of the RAND experiment (as suggested by one of the reviewers). In the methods section, we have also clarified our model presentation. Finally, we have added an appendix table (and detailed discussion) on the econometric models and findings of studies published on Vietnam's health insurance programme.

We have revised the manuscript in the light of these comments. We have provided a marked copy of the changes made in the previous article with track changes in Word. We thank the reviewers for their helpful and constructive comments, and hope that this revised version will contribute to the contents of *Social Science and Medicine*.

We look forward to your response and would be happy to answer any questions that you may have on this paper.

Sincerely,

Shehzad Ali

**Addressing care-seeking as well as insurance-seeking selection biases in estimating the impact of health insurance on out-of-pocket expenditures**

Response to reviewers' comments

**Reviewer 1**

The authors while revising the manuscript have taken into account my comments and suggestions noted when I reviewed for the first time.
I have noticed that the authors have now used the out-of-pocket cost instead of out-of-pocket expenditure. My suggestions were not to use them interchangeably as I believe they have different connotations and it also depend on the items of expenditure that are included. "Cost" has wider perspective - some of the items to be included may not have been collected during the survey. It will be useful to check what information has been collected during the data collection for the data sets used, and may be useful to note/define OOP cost or OOP exp. My suggestions would be to use out-of-pocket expenditure or out-of- pocket payments instead of OOP cost, and include definition in the text.

The authors point in reply to my point 7 when I reviewed the first submission: The generalizability of the findings for other type insurance - e.g. social insurance or compulsory health insurance is not very straight forward. What the authors have added has covered the main points, however, it is important to note there may be different situation. The participation or enrolment may be mandatory - everyone is covered with no payment at the point of use, or everyone covered with different levels of cop-payments at the point of use.

We thank the reviewer for their helpful comments. We now use the term 'out-of-pocket expenditure' which we agree is more appropriate in this context (see edits in the paper). Also, we have clarified the definition of healthcare expenditure on p.13 (under the heading 'Data').

*"Respondents were asked to recall direct health care expenditures (i.e. user fees for consultations, diagnostic tests and medicines), indirect expenditures (food and hospital stay, travel and other expenditures) and any unofficial payments (i.e. gifts to health care providers). OOP expenditure was then defined as the sum of these expenditures."*

Also, in the discussion section, we now acknowledge that the impact of health insurance and the level of selection biases depend on the type of health insurance, level of coverage and the context of the study. We have added the following paragraph in the discussion section.

*"Moreover, selection biases also depend on the type of coverage and benefits of health insurance programme as well as the study context. For instance, while compulsory health insurance programmes are generally not affected by insurance-seeking adverse selection, they may still suffer from care-seeking selection issue. In case of Vietnam, Sepehri et al (2011) evaluated both compulsory health insurance (CHI) and voluntary health insurance (VHI) programmes and found that the impact of CHI on reducing OOP healthcare expenditure was higher than VHI. This may be partly because VHI is more likely to be influenced by adverse selection. Similarly, coverage (such as type of services and health facilities covered) and level of insurance co-payment may also the impact of insurance and the influence insurance-seeking and care-seeking selection biases."*

**Reviewer 2**

I think this paper is a good report for a project, although that the results do not differ from other papers on Vietnamese insurance. I do not think it merits publication if we know the results from Vietnam well. The authors can show how this results differs from other Vietnam literature in detail. I do not think it generates any methodological interest. I had indicated this before. Here are my reasons to think the paper should not be published as it does not say much about insurance issues.

I first draw attention to Angrist and Pischke 2009. It is not clear whether one should correct for 0 expenditure. That would be an interesting discussion. Given that most people correct for this let us ask if this is anything new. The RAND experiment used a local average treatment effect (LATE) for selection into insurance to carry out:

E[y > 0, insurance] P[y>0] - E[y > 0, not insurance] P[y>0].

Angrist and Pischke raise some legitimate concerns in the insurance type model, regarding this type of model. That is the ones who do not pay at all in case of insurance may be different from those who do not pay without insurance. Thus selection of everyone on paying may be not be correct. Examine their equation 3.4.5. I don't think they reach a conclusive statement. But this is where methodological discussions lie. It would be interesting to see a fuller discussion on this. I think what they are pointing to is that selection to incur payment itself is shaped by having insurance. I would think this would be present in using the LATE; I am not sure. But these are very important issues.

Now let us suppose that the two part selection effect is a legitimate thing to be concerned about. One can say use a selection to insurance and then run a weighted PSM regression on cost that is selected through some kind censored method. This is done in a Wagstaff paper or may be in Wagstaff and Lindelow.

[PLEASE MAKE SURE THE NOTATION IS ABSOLUTELY CLEAR] Now, I cannot follow your notation. I understand models 1-3. What are 4a and 4b? You estimate 10 with IMR on the left censored cost equation. This is roughly LATE if we had randomized assignment followed by purposive uptake of insurance. This is your paper.

I am not sure what type of problems your approach may induce for the error terms. But that is indeed not the remit of SSM.

The double selections issue has been address before through PSM and as I stated in the RAND experiment. The RAND method cannot be used as you do not have a RCT. You use IMR for insurance and then use a censored estimation. This is just another method. If you carried out this using PSM weights and see differences then it would be a methodological paper. I don't think using IMR for the censored expenditure data is worthy research by itself.
I leave it to the editor to make the decision.

{PLEASE ADDRESS] At the least examine how both selection into insurance and the censored expenditure has been dealt with in the literature. I believe Acharya et al. raise this issue. If you can motivate this by going through some work on this, for example the RAND paper and most of the papers by Wagstaff and colleagues, would be a publishable paper. One way to do this is to examine how this dual selection has been done and what are the methodological issues behind it.

[PLEASE ADDRESS] A further issue is that you need to show in more detail how your findings contrast the other Vietnam insurance findings. Make a table of type of data used, the approach, and the results.

We thank the reviewer for their helpful comments. Our detailed response is presented below.

Acharya et al. (2012) report findings of a systematic review of the impact of insurance programmes in developing countries. In terms of potential biases, they found that insurance studies in developing countries mainly account for insurance-selection bias due to adverse selection and cream skimming (p. 92-93), while only a handful of studies account for the care-seeking decision (p. 45, 94). However, they do not find any studies that accounted for both types of biases. In line with their findings, and to further motivate the need for correcting for care-seeking bias by considering both extensive and intensive margins, we have now added the following in the manuscript (end of p.6).

*"In a systematic review of insurance studies in developing countries, Acharya et al (2012) found that care-seeking selection is not commonly addressed in the literature. Most studies ignore this by either using only the positive expenditure in the analysis (Jowett et al 2003), or treating zero and non-zero expenditures on the same scale without addressing the selection issue. Other insurance studies take a two-part modelling approach, separating the probability of seeking care from health care expenditure (conditional on seeking care). The following approaches have been used in the insurance literature in developing countries (Acharya et al 2012): Tobit model, two-part models and selection models. These models include the care-seeking decision in the first part followed by health expenditure equation in the second part.*

*There is a strong case for separating the probability of seeking care from health care expenditure to assess the extensive margin i.e. decisions to seek care and impact on demand for contact with the health care service, which relies mainly on individual circumstances or preferences, degree of insurance coverage and access to health care services. This is then followed by evaluating the intensive margin which is primarily an agency relationship where treatment decisions are made by the treating physician, and influenced by the organisation, quality, prices and incentives in the health care system.*

*Separating out the contributions of health insurance in extensive and intensive margins on out-of-pocket expenditures is important. For instance, total OOP expenditure could increase if the extensive margin (threshold for seeking care) decreases, as greater frequency of treatment increases total expenditure. However, the impact of decreasing threshold on OOP expenditure once care is sought could also be negative if, for instance, more timely care due to lower threshold for care seeking impacts severity of illness when care is sought and treatment needs (due to more timely intervention). On the other hand, having insurance could affect treatment decisions of the physician and patients, i.e. prescription of more intensive and/or expensive treatments or the patient is exposed to risk of supplier induced demand (as observed in case of China [18]). Therefore, it is important to explore the influence of these different factors on health care expenditures, which the selection model intrinsically enables by estimating the propensity to seek care and indicating how this impacts expenditures once care is sought."*

With regards to the Rand Health Insurance Experiment, it explored the effects of different co-payment levels and health insurance contracts (not whether individuals were insured or not) on health care utilisation. The two part model was used to disentangle the effects on the probability of seeking care i.e. the extensive margin and on health care expenditures (total and not just out of pocket) incurred given different co-payment levels.

In case of the Rand Health Insurance Experiment, the randomisation ensured that different populations exposed to varying co-payments were comparable. Hence, as the reviewer indicated, there would be no need to allow for selection bias from care-seeking across co-payment groups as we could assume randomisation balances the unobserved propensity to seek care across co-payment groups. Therefore, the observed effect of insurance on OOP expenditures for those seeking care across individuals with different co-payment levels would not be biased by differences in the unobserved propensity to seek care, which would be similar across co-payment groups due to randomisation. The estimated co-payment effects on the probability of seeking care and on health care expenditures incurred (once care is sought) would be the ATE in the population (assuming homogenous effects across the population). If the effects of co-payments were more heterogenous across the population, then the second stage effect on positive expenditures in the RAND approach would be a LATE, and as stated before, would not be biased from care seeking selection because randomisation ensures that unobserved care seeking thresholds associated with health care expenditures are balanced across co-payment groups.

However, in non-randomised setting (such as ours), we do not have comparability in observable and unobservable characteristics associated with insurance choice, the propensity to seek care and the expected health care expenditures once care is sought. In this setting, thresholds for consulting are not balanced between the two groups; hence, it is not certain that, in a homogenous treatment environment, effect of health insurance on OOP expenditure once care is sought would be the same for those that did and did not choose to receive health care. Hence, to generalise our findings and to estimate an ATE for the population of those choosing to insure and not insure (assuming a homogenous effect of insurance) we should allow for selection bias in the model for health care expenditures. The Heckman MLE also estimates an ATE and not LATE. That is, we can generalise our findings to individuals who did not seek care, which addresses the important question 'What would have been the effects of health insurance had these individuals sought care?' The allowance for care seeking selection enables us to answer that question (Madden 2008).

We have added the following paragraph in the discussion section:

*"The modelling approach used in this study is relevant to non-randomised settings evaluating the effect on insurance on OOP expenditures. Randomised studies, such as the RAND health insurance experiment which allocated individuals to different health insurance plans, are likely to have balanced groups in terms of their unobserved propensity to seek care (by virtue of randomisation). As a result, the average treatment effect can be estimated without the need to account for selection biases. However, most health insurance studies are not randomised, and therefore need to consider the issue of care seeking selection bias. Allowing for sample selection bias implies estimates can be generalised to individuals who did not seek care (Madden 2008), which addresses the important question of 'What would have been the effects of health insurance had these individuals sought care?'."*

With regards to summarising other relevant studies, including Wagstaff insurance studies, we note that these studies use PSM and difference-in-difference methods to account for insurance-seeking selection bias only; however, they do not address the care-seeking selection bias which is where this study adds to the literature. However, based on the reviewer's comment, we now provide a detailed description of methods used in the literature (see below) to correct for insurance-seeking decision.

*"A number of approaches have been used in the literature to adjust for selection bias due to insurance-purchase/participation decision. These methods can be classified based on whether they deal with selection on observable covariates (or simply observables) or unobservable covariates (or unobservables) [27]. Selection on observables is commonly addressed using regression analysis or propensity score matching [21]. The debate on regression versus matching to control for observables is not yet settled, with some authors concluding that the difference between estimates is not likely to be of major empirical significance [29]. The advantage of matching over regression is that it matches individuals based on their propensity to buy insurance by restricting the sample to observations that are comparable (at least in terms of observed characteristics). Moreover, matching methods make fewer assumptions about model specification. However, if the distribution of observed characteristics is similar in the insured and uninsured groups, and there is complete overlap between the two groups in terms of the range of propensity scores (i.e. they have common support), then regression analysis will not rely on predicting expected outcomes based on observed characteristics beyond the ranges of observable characteristics in the insured and uninsured groups, and will give similar results to regression analysis.*

*For selection on unobservables of insurance-seeking decision, a number of methods exist in the literature. These include structural models and control functions; instrumental variables; regression discontinuity; and difference-in-difference [27]. Structural models involve specifying a model to determine treatment assignment and then jointly estimating this model with the outcome (i.e. OOP expenditure). Control function approach involves separately estimating the outcome equation, and capturing insurance selection bias by including a control term (known as Inverse Mills' Ratio, explained later) from a probit model for insurance selection [34]. This approach was taken by Jowett et al (2003) [24]. Instrumental variable approach is based on finding one or more variables that predict treatment (insurance) assignment but are not directly correlated with the outcome (OOP expenditure). This approach has been used by a number of studies, including Wagstaff and Lindelow (2008) [18]. Regression discontinuity design is used when assignment to treatment changes discontinuously with respect to some threshold value which determines whether someone is in the treated (insured) or untreated (uninsured) group. This approach was used by Bauhoff et al (2011) [35] and Miller et al (2009) [36]. Difference-in-difference approach (or double differencing) involves taking the difference in outcome (i.e. OOP expenditure) between insured and uninsured groups before and after the introduction of insurance and then taking the difference in these differences. This approach requires data in both pre-treatment and post-treatment periods and can be used with longitudinal/panel data or with multiple cross-sections [37] [38]). This approach has been commonly used in the literature to control for unobserved heterogeneity associated with the insurance decision (see below).*

*Selection into insurance based on both observables and unobservables can be simultaneously dealt with by combining the above methods. For instance, regression-based models that deal with unobservables (such as Heckman sample selection model) also account for selection on observables by including observed covariates in the OOP expenditure regression model (Jowett et al 2003) [24]. Another common example of jointly addressing selection on observable and unobservables is by combining propensity score matching (for selection on observables) and difference-in-difference method (for selection on unobservables). For example, Axelson et al (2009) [39] use propensity score matching to control for observable differences between insured and uninsured, and difference-in-difference approach to control for time-invariant unobserved factors that may be correlated with outcomes. This approach has been commonly used in the insurance literature [19] [40] [41] [42].*

*Wagstaff et al (2010) [43] extend this approach by combining propensity score matching with triple differencing which involves subtracting two previous difference-in-differences in outcome measures from two later difference-in-differences measures using available data for three periods. However, the methods discussed above only account for differences in unobservables in one of the two decisions (generally the insurance-seeking decision) but not both."*

Also, we have clarified the specification of Model 4 in the paper.

Finally, for direct comparison with our study, we have reviewed papers evaluating health insurance programmes in Vietnam, including those authored by Wagstaff. As suggested by the reviewer, we have included a table (see below) which summarises the datasets and methods used in these papers as well as the results. Also, we have compared our results with these studies from Vietnam in the discussion section. The following text has been added in the paper.

*"In case of Vietnam, a number of studies have used a national dataset from different waves of the Vietnam Household Living Standard Survey (VHLSS) as well as other surveys to evaluate the impact of different types of health insurance programmes. Appendix table A3 summarises the data sources, methods and results of studies. These studies evaluated one or more of the following insurance programmes in Vietnam: (1) voluntary health insurance (VHI); (2) compulsory health insurance (CHI); (3) Vietnam Health Care Fund for the Poor (VHCFP); and (4) free healthcare for children under 6 years. These studies come to different conclusions based on the type of programme being evaluated, the dataset used and the analytical methods applied. For instance, Sepehri et al. (2006) [25] evaluated both VHI and CHI together using VHLSS for 1992-3 and 1997-8 and corrected for care-seeking bias using Tobit model (fixed and random effects) but did not account for insurance endogeneity. They found that insurance reduce OOP expenditure by 17% to 20%. Jowett et al (2003) also evaluated VHI and used the same dataset as our study, and corrected for insurance endogeneity but not care-seeking bias (and only used positive OOP expenditure observations). They found that VHI significantly reduced OOP expenditure, although their coefficients are much larger than ours results because they only used observations with positive OOP expenditures (therefore, their model results cannot be generalised to the wider population). Finally, Nguyen (2012) [6] evaluated the impact of VHI using VHLSS 2004 and 2006 using PSM and double differencing (i.e. difference-in-difference) to account for insurance selection and found that the effect of VHI on OOP expenditures is not statistically significant; however, they found that insurance increases the annual outpatient and inpatient visits by 45% and 70% respectively which partly explains no statistically significant reduction in OOP expenditure despite insurance reducing the price of care.*

*Wagstaff (2007) [55] evaluated VHCFP programme in Vietnam using VHLSS 2004 wave using propensity score matching (PSM) for insurance selection and found that insurance did not reduce the average out-of-pocket expenditure because it increased the probability and number of inpatient and outpatient visits. The same programme was evaluated by Axelson et al (2009) using PSM followed by double differencing for insurance endogeneity, and by Wagstaff (2010) using PSM followed by triple differencing to account for both observed and unobserved heterogenety (see Appendix for details). Axelson et al (2009) found that VHCFP reduced only inpatient OOP but not overall expenditure, while Wagstaff (2010) found that VHCFP reduced both inpatient OOP and total OOP expenditures. Finally, Sepehri et al (2011) evaluated CHI, VHI and VHCFP using VHLSS waves 2004 and 2006 using fixed and random effects models and found that CHI and VHI reduced OOP expenditure at district hospitals by 40% and 32% respectively but did not reduce expenditure for those using commune health centres.*

*The above studies account for observables, and in most cases also unobservable) of the insurance-seeking decision (through PSM or regression with/without difference-in-difference methods). However, none of these studies simultaneously accounted for care-seeking and insurance-seeking biases which may partly explain some of these differences in findings [56]."*

Below we present the table which we suggest should be included in the appendix.

**Table A3:** Summary of published studies evaluating the impact of health insurance in Vietnam

| Study | Data | Type of analysis | Results |
|---|---|---|---|
| Jowett *et al* (2003) | Single cross-sectional survey conducted in year 1999 using purposive sampling to evaluate the voluntary component of Vietnam's voluntary health insurance (VHI) programme – before the introduction of Vietnam Health Care Fund for the Poor (VHCFP). Survey conducted in 3 provinces (Ninh Binh, Hai Phong and Dong Thap). This data is the same as used in our paper. | Heckman's two-step regression was used to correct for insurance endogeneity. First step was a probit regression for probability of insurance. Inverse Mills Ratio (IMR) was obtained from this model and included in the OLS regression for out-of-pocket (OOP) expenditure. The expenditure equation included only non-zero values for health expenditure; hence, care-seeking selection was ignored. | Overall, health insurance was found to reduce average out-of-pocket expenditures. The dependent variable was the log of out-of-pocket expenditure. The coefficient on insurance was -2.080 (p=0.001) after correcting for insurance endogeneity which was interpreted incorrectly as 200% reduction in expenditure. |
| Sepehri *et al* (2006) | National data from 1992-3 and 1997-8 waves of the Vietnam Household Living Standards Survey (VHLSS) to evaluate Vietnam's health insurance programme; however, unlike Jowett *et al* (2003), both compulsory (predominant) and voluntary health insurance was included and jointly evaluated because VLSS did not provide distinction between the two types. | Two approaches were used with panel individual effect: (1) Tobit model which treats zero expenditure as censored (i.e. censored value for selecting into care, not insurance); and (2) truncated regression which uses only positive expenditure. Fixed and random effects models were used.<br><br>Insurance endogeneity bias was not taken into account, partly because both compulsory and voluntary insurance was included. | Random and fixed effects models produce different results. Final set of results show that health insurance reduces out-of-pocket health expenditure (between 17 and 20%). |
| Wagstaff (2007) | National data from VHLSS 2004. The study evaluated VHCFP which was introduced in 2003. | Propensity score matching was used to account for insurance endogeneity, followed by regression weighted by propensity score weights. | Total out-of-pocket health spending is reduced by VHCFP in the simple PSM but not with the regression. The study concluded that VHCFP did not reduce the average out-of-pocket |

| Study | Data | Type of analysis | Results |
|---|---|---|---|
| | | | spending because it increased the probability and the number of inpatient and outpatient visits. A secondary finding was that VHCFP reduced the risk of catastrophic spending by 3-4%. |
| Axelson *et al* (2009) | VHLSS data from 2002 (pre-VHCFP) and 2004 (post-VHCFP) | First analysis used PSM for selection into insurance followed by single differencing (i.e. difference in OOP between insured and uninsured at one time point) in a cross-section analysis of VHLSS 2004. Second analysis used PSM followed by double differencing (or difference-in-difference, i.e. first calculating the mean difference in outcome before and after the intervention for the insured and uninsured groups separately, followed by calculating the difference between the mean differences of the two groups). This is done using panel dataset for VHLSS 2002 and 2004; the double differencing is to take account of time-invariant unobserved factors. | The result from the double differencing differs from single-differencing. Single differencing found statistically significant reduction in OOP at household level by 19% (although reduction in per capita expenditure of 14% was not significant). Results of difference-in-difference also found reduction in health care expenditure but they were only significant for inpatient care expenditure (absolute reduction of 134.6 Vietnamese Dong). |
| Wagstaff (2010) | VHLSS data from the panel element of the 2002, 2004 and 2006 waves. | Triple-differencing which involves difference-in-difference over three periods, i.e. besides the double difference-in-difference between insured and uninsured (as above), a further difference is taken to 'net out' the difference between the same groups in the change in mean OOP over an earlier period. Instead of assuming parallel trends in the unobservables for the insured and uninsured groups, it assumes that the change in unobservables for each group in the two periods (2002-2004) and (2004-2006) is the same. This method can be used with regression or matching to control for observables. | Single-difference with matching found no significant impact of VHCFP on out-of-pocket spending. Double and triple-differencing found significant negative impact on total OOP expenditure (-181 and -327 VND respectively) and OOP expenditure on inpatient care (-131 and -248 VND respectively). |

| Study | Data | Type of analysis | Results |
|---|---|---|---|
| | | The proposed method estimates programme impact on those covered by it but not those currently not covered. | |
| Sepehri *et al* (2011) | VHLSS data from the panel element of the 2004 and 2006 waves. The focus is on compulsory health insurance (CHI), VHI and insurance for the poor. | Fixed and random effects models were used. Fixed effects analysis was intended to control for time-invariant unobserved individual effects. Endogeneity bias due to adverse selection into insurance was not taken into account. | Random effects analysis showed that CHI and VHI reduce OOP spending by about 24% while health insurance for the poor reduces it by 15%. However, in the fixed effects analysis, the coefficients for CHI and VHI were not significant. Further analysis showed that CHI and VHI reduce OOP expenditures by 40 and 32%, respectively for those using district hospitals but not significant for commune centres. |
| Nguyen (2012) | VHLSS data from the panel element of the 2004 and 2006 waves. The focus is on voluntary health insurance. | PSM followed by double differencing (i.e. difference-in-difference). | The effect of voluntary health insurance on out-of-pocket expenditure on health care services is not statistically significant; however, insurance increases the annual outpatient and inpatient visits by 45% and 70% respectively which partly explains no statistically significant reduction in OOP despite insurance reducing the price of care. |
| Nguyen and Wang (2013) | VHLSS data from the panel element of the 2004 and 2006 waves. The focus was on evaluating a government policy to provide free healthcare for children younger than 6 years. The policy came into effect in the beginning of 2005. | Difference-in-difference approach using VHLSS wave 2004 (pre-policy) and 2006 (post-policy) in a regression model controlling for potential confounders. | Free health insurance reduced OOP health expenditure by US$5.09 in the age group 4-7. It also reduced the probability of having catastrophic OOP expenditure by 1.7 percentage point. |

Highlights

- Out-of-pocket (OOP) expenditure on health care depends on the care-seeking decision which in turn may depend on the expected expenditure
- Studies measuring the impact of health insurance on OOP expenditure ignore selection bias due to non-random care-seeking decision
- We propose a double-selection model using Heckman approach to address both care-seeking and insurance-seeking selection biases
- We found that the impact of health insurance was underestimated by 21 percentage points when selection biases were ignored
- Our findings are important for future studies aiming to estimate the impact of health insurance without selection biases

**TITLE PAGE**

| | |
|---|---|
| **Title of the paper** | Addressing care-seeking as well as insurance-seeking selection biases in estimating the impact of health insurance on out-of-pocket expenditure~~costs~~ |
| **Running head** | Addressing care-seeking as well as insurance-seeking selection biases |
| **Tables** | 2 |
| **Figures** | 2 |
| **Appendix tables** | 3~~2~~ |
| **Conflict of interest** | None |

## ABSTRACT

Health Insurance (HI) programmes in low-income countries aim to reduce the burden of individual out-of-pocket (OOP) health care ~~cost~~expenditure. However, if the decisions to purchase insurance and to seek care when ill are correlated with the expected healthcare expenditure~~cost~~, the use of naïve models may produce biased estimates of the impact of insurance membership on OOP ~~cost~~expenditure~~s~~. Whilst many studies in the literature have accounted for the endogeneity of the insurance decision, the potential selection bias due to the care-seeking decision has not been taken into account. We extend the Heckman selection model to account simultaneously for both care-seeking and insurance-seeking selection biases in the healthcare expenditure ~~a cost of care~~ regression model. The proposed model is illustrated in the context of a Vietnamese HI programme and results compared with those of alternative models making no or partial allowance for selection bias. In this illustrative example, the impact of insurance membership on reducing OOP expenditures ~~costs~~ was underestimated by 21 percentage points when selection biases were not taken into account. We believe this is an important methodological contribution that will be relevant to future empirical work.

**Key words:** Health insurance; selection bias; endogeneity; Heckman model; low-income countries

## 1. INTRODUCTION

Out of pocket (OOP) payment is the predominant mechanism of health care financing in most low-income countries, accounting for over half of the total expenditure on health in low income countries [1]. These payments create financial barriers to health care access, especially for the poor, often resulting in long delays in seeking care until disease severity has progressed so far that much prolonged and expensive treatment is required [2]. Van Doorslaer et al (2007) [3] found that, among Asian countries, reliance on OOP payments was highest in Vietnam and India, where >80% of total health expenditures were funded by OOP expenditures~~payments~~. In the same study, Vietnam also had the highest proportion of individuals incurring catastrophic payments; this was reported to be 34%, 15% and 8.5% at threshold levels of 5%, 10% and 15% of total household expenditure.

In recent decades, many low-income countries have embarked on voluntary health insurance (VHI) programmes commonly characterised as not-for-profit, voluntary membership schemes with affordable, community-rated premia for all individuals. They may be organised at local or regional levels, like SEWA and ACCORD in India [4] and Grameen in Bangladesh [5], or at national level, like in Vietnam [6], Ghana [7] and Mexico [8]. The overarching aim of VHI programmes is to reduce the burden of out-of-pocket expenditures~~payments~~, and in turn provide financial protection to the target population. Based on the same principle, recent policy focus has been on providing universal health coverage (UHC) which entitles all people to access health care funded through publicly organised risk pooling [9]. Most high income countries already have some form of UHC while many middle and low-income countries (LMIC) are making significant progress in this direction [10] [11]. However, coverage in most LMICs is far from universal, both in terms of enrolment rates and the level of financial protection [11]. Moreover, use of care among the enrolled is often restricted by geographical access and co-payment contributions, resulting in forgone necessary care [12].

Several studies in recent years have focused on monitoring progress and evaluating effectiveness of various forms of risk pooling in providing financial protection (note: from hereon we will use the generic term 'health insurance' for all forms of risk pooling). While most studies found a positive effect of health insurance on reducing OOP expenditures ~~spending~~ [13] [8] [14] [15] [16] [17], some studies found mixed, negative or no significant effect [18] [19] [20]. Systematic reviews focusing on performance of health insurance have found positive, mixed or inconclusive evidence on financial protection [21] [22] [23].

To measure the impact of health financing programmes on OOP, robust and consistent methods are required. The available evidence on the impact of insurance on OOP expenditures ~~payments~~ may have limitations due to differences in quantitative methodologies employed in evaluation studies. It has been noted in the literature that when the analysis is based on observed OOP ~~cost~~expenditures, it may be biased due to individual-level selection decisions that influence the level of incurred expenditure~~costs~~ [24] [25] [26]. Two selection decisions are particularly important in the context of evaluating the impact of health insurance on OOP expenditures ~~costs~~ in low-income countries. These are insurance-seeking and care-seeking selection decisions. Both decisions are determined by observable and unobservable characteristics that may also be correlated with expenditure ~~cost of~~on health care. It is now common for studies of the impact of VHI on OOP expenditure ~~costs~~ to allow for insurance-seeking bias due to adverse selection (based on both observable and unobservable characteristics). However, previous studies have not allowed for care-seeking selection bias. This study is innovative in allowing simultaneously for these two potential sources of bias. Our study extends the selection models to simultaneously correct for selection bias due to insurance-seeking as well as care-seeking decisions. The aim of this study is to illustrate this approach to estimate the impact of health insurance on OOP expenditure ~~costs~~ using observational data. We compare the results with those of alternative models that allow for selection biases only partially or not at all. For the purpose of illustration, this study uses data from a cross-sectional household survey of three provinces of Vietnam, conducted during the year 1999. However, the focus of this study is methodological.

The remaining paper is organised as follows. Section 2 discusses how care-seeking and insurance-seeking selection decisions may potentially bias OOP health care expenditure~~cost~~ analysis. This is followed by some brief background on the Vietnamese voluntary health insurance programme, to help put the empirical results into context. Section 3 discusses the data and the econometric models employed in this analysis. Section 4 presents the results of econometric analysis, and finally, section 5 discusses the implications of the study findings.

## 2. SELECTION BIASES IN MEASURING THE IMPACT OF VHI

When selection decisions are correlated with the OOP expenditure~~cost~~ of health care due to observable or unobservable characteristics, as discussed in detail below, the estimate of the impact of health insurance on OOP expenditure~~cost~~ of care may be biased [27]. One potential source of bias is insurance selection. For example, individuals may be more likely to purchase insurance if they expect high future healthcare expenditures~~costs~~, i.e. voluntary insurance may be prone to adverse selection. This is also relevant to health financing programmes that are moving in the direction of universal health coverage; these programmes often include an element of choice for the enrolment decision which can be influenced by expected future healthcare expenditures~~costs~~. If so, then the insured may have greater health care needs and in turn higher expenditure ~~costs~~ than the uninsured, even after allowing for observed characteristics such as age, sex and self-reported health. In this case, the mean difference in OOP expenditure~~cost~~ between insured and uninsured groups will under-estimate the causal impact of VHI on reducing OOP health care expenditure~~cost~~.

A second source of selection bias is attributable to the care-seeking decision. When an individual is sick and in need of health care, they make a decision to seek care or not, i.e. they face the care-seeking decision hurdle. For example, individuals may be less likely to seek care if they expect the expenditures ~~costs~~ to be high relative to the benefits, given their household financial situation. This in turn influences whether or not their health care expenditure~~cost~~ is observed. If the care-seeking decision is correlated with health care expenditures~~costs~~, then not accounting for the care-seeking selection in healthcare expenditure ~~cost~~ model may bias the estimates. Moreover, the factors associated with the care seeking decision may be associated with the insurance decision.

Selection bias may occur due to observable or unobservable characteristics (i.e. confounders) that are also correlated with the outcome of interest. Selection on observables, such as age and gender, can be solved by using regression or matching methods [28]. These are commonly known as “control strategies” as they control for difference in characteristics between those who self-selected and those who did not, to allow causal inference [29]. However, regression and matching methods do not account for selection on unobservable factors that may be correlated with health care expenditures~~costs~~. It is this selection on unobservables which is the focus of this paper. For this, the common approaches include instrumental variables, control functions and the joint estimation of outcome and selection in a structural approach [27].

While some studies in the literature have acknowledged but not accounted for potential biases due to unobservable characteristics [26, 30], others have corrected for insurance selection only and not for care-seeking selection [25] [24] [18] [31]. We start with a more detailed discussion of the possible causes and impact of the two forms of selection bias.

### 2.1. Care-seeking selection and its impact on OOP ~~ost~~expenditure

Care-seeking selection bias is a form of sample selection bias that occurs when the outcome of interest (in this case, the health care expenditure~~cost~~) is only observed for a sub-sample of the population that meets some criterion defined with respect to a selection decision (in this case, the care-seeking decision), and this selection decision is in turn associated with the outcome of interest [32] [33]. Hence, in the case of health care expenditure ~~cost~~ analysis, only a subsample of the sick population may seek care and in turn incur health care expenditures~~cost~~. If the care-seeking decision is not random but is associated with the expected healthcare expenditure~~of care~~, then we have selection problem. However, if all determinants of care-seeking decision (that are correlated with the outcome) are observed and included in the outcome (OOP expenditure) regression, then we have accounted for this selection bias. On the other hand, if the decision to seek care ~~care-seeking decision~~ is correlated with OOP expenditure through unobserved factors~~not known to the analyst~~, then the estimated coefficients in the expenditure model (including the coefficient on insurance membership), based on observed expenditure~~cost~~, may be biased. Not accounting for this selection will result in coefficient estimation based on a non-random sample. As a result, the observed effect of insurance on OOP expenditure will not be generalisable to the population who did not seek care. Therefore, to evaluate the policy impact of expanding insurance coverage (and hence access to care) to the entire population, it is important to account for selection bias induced by care seeking.

For example, an individual's degree of risk aversion with respect to health outcomes may be an unobserved factor associated with a higher probability of seeking care given illness and also with lower expenditure ~~cost~~when care is sought. To put this the other way around, the subsample of individuals who seek care and have positive expenditures~~cost~~ may be more risk averse and face relatively low expenditures of care. Hence, if risk attitude is not taken into account, health care expenditure may be under-estimated when extrapolating estimates of effects to the wider population of potential health care users. Secondly, because insurance reduces the price of health care and therefore increases the demand for health care, the insured may be more likely to seek care and in turn have ~~observing~~ their positive health care expenditures~~cost~~ observed. If so, then the expenditure analysis will under-estimate the impact of expanding VHI to the wider population, on reducing OOP healthcare expenditures when care is sought. Wagstaff and Lindelow (2008) [18] found evidence of this during analysis of three household surveys in China. They found that after controlling for insurance-seeking bias, insurance membership was associated with an increased risk of high healthcare spending. They concluded that this is because insurance increased the probability of seeking care when ill which resulted in higher ~~cost~~expenditures in the insured group; therefore, an evaluation of the impact of voluntary insurance should take account of care-seeking behaviour.

In a systematic review of insurance studies in developing countries, Acharya et al (2012) [21] found that care-seeking selection is not commonly addressed in the literature. Most studies ignore this by either using only the positive expenditure in the analysis [24], or treating zero and non-zero expenditures on the same scale without addressing the selection issue. Other insurance studies take a two-part modelling approach, separating the probability of seeking care from health care expenditure (conditional on seeking care). The following approaches have been used in the insurance literature in developing countries [21]: Tobit model, two-part models and selection models. These models include the care-seeking decision in the first part followed by health expenditure equation in the second part.

There is a strong case for separating the probability of seeking care from health care expenditure to assess the extensive margin i.e. decisions to seek care and impact on demand for contact with the health care service, which relies mainly on individual circumstances or preferences, degree of insurance coverage and access to health care services. This is then followed by evaluating the intensive margin which is primarily an agency relationship where treatment decisions are made by the treating physician, and influenced by the organisation, quality, prices and incentives in the health care system.

Separating out the contributions of health insurance in extensive and intensive margins on out-of-pocket expenditures is important. For instance, total OOP expenditure could increase if the extensive margin (threshold for seeking care) decreases, as greater frequency of treatment increases total expenditure. However, the impact of decreasing threshold on OOP expenditure once care is sought could also be negative if, for instance, more timely care due to lower threshold for care seeking impacts severity of illness when care is sought and treatment needs (due to more timely intervention). On the other hand, having insurance could affect treatment decisions of the physician and patients, i.e. prescription of more intensive and/or expensive treatments or the patient is exposed to risk of supplier induced demand (as observed in case of China [18]). Therefore, it is important to explore the influence of these different factors on health care expenditures, which the selection model intrinsically enables by estimating the propensity to seek care and indicating how this impacts expenditures once care is sought.

To understand all this mathematically, let the health care ~~cost~~expenditure model be expressed as:

$$Expenditure\cancel{Cost}_i = \alpha + \beta_1(Insurance)_i + \beta_x X_i + \varepsilon_i^Y \qquad (1)$$

Here $X$ is a vector of observed variables and $\varepsilon_i^Y$ represents the unobserved predictors of ~~cost~~expenditure. ~~Cost~~Expenditure is only observed to be positive if an individual seeks health care, i.e. ~~cost~~expenditure depends on an endogenous care-seeking decision ($CS_i$) such that:

$$Expenditure\cancel{Cost}_i \begin{cases} = \ +ve \ \ if\ Care - seeking = Yes \\ \ \ = 0\ \ if\ Care - seeking = No \end{cases} \qquad (2)$$

The probability of care-seeking, in turn, can be estimated as a probit model (3):

$$\Pr[Care - seeking] = \ \Phi(\beta_z Z_i + \ \varepsilon_i^{cs}) \qquad (3)$$

Here $\Phi$ represents the distribution of probit model and $Z$ represents the observed predictors of care-seeking decision, including insurance status. Expenditure is positive if latent propensity ($\beta_z Z_i$) to seek care exceeds the unobserved threshold for an individual.

If the unobserved predictors in the error terms of equations (1) and (3) are not independent of each other, then it implies that the observed ~~cost~~expenditure on~~of~~ health care (and the estimated coefficients in ~~cost~~expenditure regression) depends on the care-seeking process. This endogenous dependence of the error term violates one of the fundamental assumptions of least squares regression and gives rise to sample selection bias. Heckman (1977) [34] explains that this selection bias stems from the common problem of omitted variable bias, i.e. a situation whereby the model is missing one or more important predictors that are correlated with the selection decision as well as the outcome equation. The presence of omitted variable bias is then compensated by over- or under-estimating the coefficients of the observed factors in the model, such as the insurance variable in this case. As a result, estimated effects on the impacts of health insurance on OOP expenditures are unlikely to be generalisable to the wider population who were not observed to incur OOP expenditure.

### 2.2. Insurance-seeking selection

Voluntary health insurance programmes often attract sicker or more risk-averse individuals, i.e. insurance-purchase/participation decision is not randomly distributed in the population. While regression analysis can control for age, sex and other observed factors, it cannot allow for unobserved aspects of the individual's health, preferences and environment that influence both health care ~~cost~~expenditures and the insurance-purchase/participation decision. Insurance status may influence both the care-seeking decision and the healthcare ~~cost~~expenditure. If part of this influence occurs through the unobserved determinants of the insurance-purchase/participation decision that are correlated with healthcare ~~cost~~expenditure equation, then insurance status is not exogenous to the model. This would violate the classical exogeneity assumption of linear regression, and the model would suffer from endogeneity bias.

A number of approaches have been used in the literature to adjust for selection bias due to insurance-purchase/participation decision. These methods can be classified based on whether they deal with selection on observable covariates (or simply observables) or unobservable covariates (or unobservables) [27]. Selection on observables is commonly addressed using regression analysis or propensity score matching [21]. The debate on regression versus matching to control for observables is not yet settled, with some authors concluding that the difference between estimates is not likely to be of major empirical significance [29]. The advantage of matching over regression is that it matches individuals based on their propensity to buy insurance by restricting the sample to observations that are comparable (at least in terms of observed characteristics). Moreover, matching methods make fewer assumptions about model specification. However, if the distribution of observed characteristics is similar in the insured and uninsured groups, and there is complete overlap between the two groups in terms of the range of propensity scores (i.e. they have common support), then regression analysis will not rely on predicting expected outcomes based on observed characteristics beyond the ranges of observable characteristics in the insured and uninsured groups, and will give similar results to regression analysis.

For selection on unobservables of insurance-seeking decision, a number of methods exist in the literature. These include structural models and control functions; instrumental variables; regression discontinuity; and difference-in-difference [27]. Structural models involve specifying a model to determine treatment assignment and then jointly estimating this model with the outcome (i.e. OOP expenditure). Control function approach involves separately estimating the outcome equation, and capturing insurance selection bias by including a control term (known as Inverse Mills' Ratio, explained later) from a probit model for insurance selection [34]. This approach was taken by Jowett et al (2003) [24]. Instrumental variable approach is based on finding one or more variables that predict treatment (insurance) assignment but are not directly correlated with the outcome (OOP expenditure). This approach has been used by a number of studies, including Wagstaff and Lindelow (2008) [18]. Regression discontinuity design is used when assignment to treatment changes discontinuously with respect to some threshold value which determines whether someone is in the treated (insured) or untreated (uninsured) group. This approach was used by Bauhoff et al (2011) [35] and Miller et al (2009) [36]. Difference-in-difference approach (or double differencing) involves taking the difference in outcome (i.e. OOP expenditure) between insured and uninsured groups before and after the introduction of insurance and then taking the difference in these differences. This approach requires data in both pre-treatment and post-treatment periods and can be used with longitudinal/panel data or with multiple cross-sections [37] [38]). This approach has been commonly used in the literature to control for unobserved heterogeneity associated with the insurance decision (see below).

Selection into insurance based on both observables and unobservables can be simultaneously dealt with by combining the above methods. For instance, regression-based models that deal with unobservables (such as Heckman sample selection model) also account for selection on observables by including observed covariates in the OOP expenditure regression model (Jowett et al 2003) [24]. Another common example of jointly addressing selection on observable and unobservables is by combining propensity score matching (for selection on observables) and difference-in-difference method (for selection on unobservables). For example, Axelson et al (2009) [39] use propensity score matching to control for observable differences between insured and uninsured, and difference-in-difference approach to control for time-invariant unobserved factors that may be correlated with outcomes. This approach has been commonly used in the insurance literature [19] [40] [41] [42]. Wagstaff et al (2010) [43] extend this approach by combining propensity score matching with triple differencing which involves subtracting two previous difference-in-differences in outcome measures from two later difference-in-differences measures using available data for three periods.

However, the methods discussed above only account for differences in unobservables in one of the two decisions (generally the insurance-seeking decision) but not both.

To put this mathematically, the insurance-seeking decision can be represented by a probit model:

$$\Pr[Insurance = 1] = \Phi(\beta_v V_i + \varepsilon_i^{INS}) \qquad (4)$$

Here $V$ represents the predictors of insurance-seeking decision. Selection bias arises when there is correlation the error terms in equation 4 and equation 1, or between the error terms in equation 4 and equation 3.

Finally, the unobserved factors associated with the care seeking decision may be associated with the purchase of insurance. This paper proposes a regression-based method to account simultaneously for both care-seeking and insurance-seeking selection biases.

## 3. DATA AND METHODS

For the purpose of illustrating our methods, we use household survey data from Vietnam collected in the year 1999. These data were originally analysed by Jowett et al (2003) [24]. However, those authors only accounted for insurance-purchase/participation selection and did not take account of care-seeking selection bias. Our study illustrates how to jointly account for both insurance-purchase/participation and care-seeking selection biases. We provide a short paragraph of background on the Vietnamese health insurance programme below, to help readers understand the policy context of this illustrative empirical analysis.

Vietnam introduced health sector reforms in the 1980s, which resulted in the introduction of user fees for services that were previously available free of charge. Between 1993 and 1998, public sector user fees rose by over 1,000% in real terms. During the same time period, fees for private health professionals rose by almost 600%. In 1993, Vietnam introduced its health insurance programme, which included compulsory health insurance for civil servants, and voluntary health insurance (the subject of this analysis) for formal and informal sector employees, the unemployed and children. In 1998, about 12% of the Vietnamese population were covered by the insurance programme, with a little over half covered by the VHI programme [44].

### 3.1. Data

The data and sampling methods are described in detail in Jowett et al (2003) [24] and briefly summarised here. Data were collected through one-to-one questionnaire-based interviews conducted in three provinces with reasonably high membership rates, i.e. Hai Phong and Ninh Binh in the north-east and Dong Thap in the south-west. Within each province, one urban and two rural districts were randomly sampled, followed by random sampling of three communes within each district, followed by random sampling of insured and uninsured individuals with each commune. A total of 1,650 adults and 1,101 children were interviewed, of which 19% were residents of Ninh Binh, 40% of Hai Phong and 41% of Dong Thap. The survey collected data on baseline demographics, health insurance status, health care utilisation, out of pocket payments and self-reported health status for the three months period prior to the interview. The socioeconomic status of the respondent was recorded using annual household consumption expenditure in the last 12 months, which was adjusted for the household size using the following equivalence scale [45]:

$$Equivalence\_factor = (No.of\ adults + \emptyset * No.of\ children)^{\theta} \quad (5)$$

Following Wagstaff et al (1999) [46], the two unknown parameters $\emptyset$ and $\theta$ were set equal to 0.5. Since the proportion of insured individuals in the population was small, the survey design oversampled the insured members by increasing their sampling frequency. For the purpose of analysis, sampling weights were used to account for the sampling structure.

From a total sample of 2,751 interviewees, 1,192 individuals reported being ill in the past three months, of whom 985 sought health care and incurred out of pocket ~~cost~~expenditure. Respondents were asked to recall direct health care expenditures ~~costs~~ (i.e. user fees for consultations, diagnostic tests and medicines), indirect expenditures ~~costs~~ (food and hospital stay, travel and other ~~cost~~expenditures) and any unofficial payments (i.e. gifts to health care providers). OOP expenditure was then defined as the sum of these expenditures~~; total costs were used~~ in the analysis. Data on insurance premiums had substantial non-responses, possibly because many individuals purchased their policy several months before the survey. Therefore, following Jowett et al (2003) [24], the premium amount was not included in estimations of healthcare ~~cost~~expenditures for the insured. The resulting underestimation of ~~cost~~expenditures for the insured is unlikely to be substantial, given the low level of premiums relative to average health ~~cost~~expenditures amongst insured patients[24]. However, this does not matter for our methodological purposes of illustrating the differences between standard methods and our proposed new method of allowing for care-seeking and insurance-seeking selection when estimating out of pocket ~~cost~~expenditures. The lack of complete data on premia paid does however mean that the "true" impact of VHI on reducing total health care ~~cost~~expenditures will be slightly over-estimated by both the standard and the proposed models.

## 3.2. Econometric models

We used four approaches to model the impact of VHI on out of pocket health care ~~cost~~expenditure. The approaches differed in terms of whether or not the model accounted for care-seeking and insurance-seeking selection biases. All models take as their dependent variable the log of the observed individual-level out of pocket ~~cost~~expenditure on~~of~~ health care. Individuals who did not seek health care, despite reporting illness, had zero observed ~~cost~~expenditure. Since the log of zero is undefined, a positive constant (+1) was added to the ~~cost~~expenditure for all individuals. Household consumption expenditure was also log-transformed because of the skewed distribution. All models used heteroskedasticity-robust standard errors. The econometric models are described below.

### 3.2.1. Model 1: Ordinary Least Squares (OLS) model for ~~cost~~expenditure on~~of~~ care

Model 1 is a naïve OLS regression represented by equation 1; it uses (log) observed health care ~~cost~~expenditure for both care-seeking and non-care-seeking individuals.

$$Expenditure\cancel{Cost}_i = \alpha + \beta_1 (Insurance)_i + \beta_x X_i + \varepsilon_i^Y \qquad (1)$$

Since the ~~cost~~expenditure on~~of~~ care equation is semi-logarithmic, the coefficient on insurance variable was transformed using equation (6) [47] to estimate the percentage impact of insurance on ~~cost~~expenditure on~~of~~ care.

$$Transformed\_coefficient = \exp\left(\beta - \frac{1}{2}Var(\beta)\right) - 1 \qquad (6)$$

Here $\beta$ is the untransformed regression coefficient on the insurance variable and *var*($\beta$) is the variance of the untransformed coefficient. The coefficient on the insurance variable represents the impact of insurance membership on out-of-pocket ~~cost~~expenditure. The OLS model ignores selection on unobservables resulting in care-seeking and insurance-seeking self-selection biases.

### 3.2.2. Model 2: Heckman's sample selection model to account for care-seeking selection only

Model (2) accounts for care-seeking selection bias by using Heckman's sample selection approach that jointly estimates the care-seeking decision and the ~~cost~~expenditure equation (OLS) conditional on care-seeking. This model involves two equations: (a) a care-seeking sample selection equation that models the selection decision [equation 3]; and (b) a ~~cost~~expenditure equation using log of health care ~~cost~~expenditure for individuals who sought care [equation 7], i.e. the dependent variable is non-zero ~~cost~~expenditure conditional on seeking care.

$$\Pr[Care - seeking] = \Phi(\beta_z Z_i + \varepsilon_i^{cs}) \qquad (3)$$

$$Expenditure\cancel{Cost}_i \,|\, (care - eseeking = 1) = \alpha + \beta_1 (Insurance)_i + \beta_x X_i + \varepsilon_i^h \qquad (7)$$

Heckman's model jointly estimates equations (3) and (7) using maximum likelihood estimation, which allows for correlation between the unobserved determinants of the care-seeking decision and the healthcare ~~cost~~expenditure ~~of care~~ equation (correlation coefficient $\rho$). The model was identified using functional form assumptions about joint normality in correlation of the error terms However, this model only accounts for care-seeking selection but ignores the insurance selection bias.

### 3.2.3. Model 3: Treatment effects model to account for insurance selection only

To account for the endogeneity of the insurance decision, Heckman's treatment effects model is commonly used [25] [24] [18] [31]. The treatment effects model also contains two equations: (a) a selection equation which models the insurance-seeking decision [equation 4]; and (b) an unconditional ~~cost~~expenditure equation [equation 1] which uses log of health care ~~cost~~expenditure for both insured and uninsured individuals for both care-seeking and non-care seeking individuals.

$$\Pr[Insurance = 1] = \Phi(\beta_v V_i + \varepsilon_i^{INS}) \qquad (4)$$

$$Expenditure\cancel{Cost}_i = \alpha + \beta_1 (Insurance)_i + \beta_x X_i + \varepsilon_i^Y \qquad (1)$$

The treatment effects model jointly estimates the insurance-seeking probit model and the healthcare ~~cost~~expenditure ~~of care~~ model using maximum likelihood estimation. This allows for correlation between the unobserved determinants of the insurance decision and the healthcare ~~cost~~expenditure ~~of care~~ equation. As noted by Wagstaff et al. (2010) [43], the model makes the assumption that there are no further unobserved benefits from insurance for individuals who choose insurance (i.e. the estimates of the effect of insurance for the insured can be generalised to the uninsured if they were to receive insurance). However, the treatment effects model ignores the care-seeking selection bias. It further differs from Heckman's sample selection model (model 2) in two aspects: (a) the endogenous choice variable (i.e. insurance variable) directly enters the outcome (~~cost~~expenditure) regression; and (b) ~~cost~~expenditure is observed for both choice groups (i.e. insured and uninsured).

The treatment effects model relies on uniquely identifying the insurance selection process [equation 4] from the outcome equation [equation 1] using predictors, also known as instrumental variables (or simply instruments), that uniquely predict the selection decision, i.e. they are correlated with the insurance decision but uncorrelated with OOP expenditures~~costs~~ except through their effect on insurance. In the current study, the following binary variables were used as instrumental variables to identify the insurance-seeking decision: 'respondent knows that VHI subsidises drugs ~~cost~~expenditures'; 'respondent knows where to buy VHI card'; 'respondent is a member of other mass/community organisation'; 'respondent has medium to high level of worry about personal future health'. Also, since insurance membership was sought more than three months before the survey, the following variables are used to identify the healthcare ~~cost~~expenditure ~~of care~~ (outcome) equation: 'hospital inpatient stay in the last three months' and 'the number of illnesses in the last three months'.

#### 3.2.4. Model 4: Two part selection model to account for both care-seeking and insurance-seeking biases

The previous two models separately corrected for either care-seeking or insurance-seeking selection bias, but not both. Since the healthcare ~~cost~~expenditure ~~of care~~ model can potentially suffer from both kinds of biases, a dual-selection model (model 4) is proposed here to jointly account for the two selection decisions.

The model has two selection-correction parts:

- The first part is an insurance decision model – this is simply the insurance probit model which is presented in the equation below (same as equation 4 before):

$$\Pr[Insurance = 1] = \Phi(\beta_v V_i + \varepsilon_i^{INS}) \qquad (4)$$

This insurance decision model is used to estimate the so-called Inverse Mills' Ratio (IMR) ($\lambda i$) for each person in the sample. IMR represents the unobserved propensity to purchase/participate in insurance, given that insurance was available. If, based on known characteristics, the predicted probability of insurance-seeking is high and the individual is observed to have purchased/participated insurance, then the influence of unobserved variables (and hence the IMR) would be small, and vice versa [48]. It can be represented mathematically as:

$$\lambda_i = \begin{cases} \phi_i(\beta_v V) \big/ \Phi_i(\beta_v V) & \text{for insured} \\ \phi_i(\beta_v V) \big/ [1 - \Phi_i(\beta_v V)] & \text{for } uninsured \end{cases} \qquad (8)$$

IMR is then used in the second part of the model (see below) to account for unobserved propensity of purchasing/participating in insurance. As before, equation (4) is estimated with exclusion restrictions, (instrumental) variables that uniquely predict insurance membership but not care-seeking or OOP expenditures (i.e. the second part of this model).

- The second part is the~~(4a) insurance decision model; and (4b)~~ Heckman sample selection model for the care-seeking decision – this is the same as ~~(same as~~ model 2 (presented earlier) but this time augmented by a correction term known as Inverse Mills Ratio ~~(IMR, see below),~~ which is obtained from the first component of the model above~~(a)~~. This IMR term is used as a covariate in both the care-seeking and OOP expenditure~~cost~~ parts of Heckman selection model (model 2).

~~Hence, part (4a) of the model is a probit equation (below) for the insurance-seeking decision [same as equation 4].~~

$$\cancel{\Pr[Insurance = 1] = \Phi(\beta_v V_i + \varepsilon_i^{INS}) \qquad (4)}$$

~~As before, equation (4) is estimated with exclusion restrictions, i.e. (instrumental) variables that uniquely predict insurance membership but not care seeking and OOP cost outcomes. This equation is then used to calculate the IMR for the insurance decision as below.~~

$$\cancel{\lambda_i = \begin{cases} \phi_i(\beta_v V) \big/ \Phi_i(\beta_v V) & \text{for insured} \\ \phi_i(\beta_v V) \big/ [1 - \Phi_i(\beta_v V)] & \text{for } uninsured \end{cases} \qquad (8)}$$

~~IMR represents the unobserved propensity to seek insurance, given that insurance was available. If, based on known characteristics, the predicted probability of insurance-seeking is high and the individual is observed to have sought insurance, then the influence of unobserved variables (and hence the IMR) would be small, and vice versa [40].~~

~~Part (4b) of the model is the Heckman sample selection model (the same as model 2). However, this time both the care-seeking and cost of care equations also include the IMR term from the insurance probit.~~ The reason for using IMR from the selection (insurance) equation in the outcome equation is that selection bias is essentially an omitted variable bias, which occurs due to unobserved factors that predict insurance decision and are also correlated with care-seeking decision and OOP expenditure~~cost~~. Inclusion of the IMR term as a covariate in the care-seeking and OOP expenditure~~cost~~ equations helps to capture the correlation between unobserved predictors of insurance and outcome equations and therefore helps to correct for the selection bias. If the IMR in the ~~cost~~expenditure equation is significant and negative, it implies a negative correlation between unobservables in the insurance participation and OOP expenditure~~cost~~. In other words, unobserved factors that decrease insurance participation will also tend to reduce OOP ~~cost~~expenditure. Hence, the final ~~cost~~healthcare expenditure ~~of care~~ equation accounts for the insurance-seeking selection through the inclusion of the IMR from the first part (4a) of the model (i.e. the insurance probit) and also accounts for care-seeking selection by jointly estimating the ~~cost~~expenditure and care-seeking equations in the second part to allow for error correlation.

The final care-seeking and OOP expenditure~~cost~~ equations are estimated jointly using Heckman's sample selection correction maximum likelihood model ~~approach~~ can be represented as:

$$\Pr[Care - seeking] = \Phi(\beta_z Z_i + \beta_s IMR + \varepsilon_i^{cs}) \qquad (9)$$

$$Expenditure\cancel{Cost}_i \mid (care - \cancel{c}seeking = 1) = \alpha + \beta_1 (Insurance)_i + \beta_x X_i + \beta_c IMR + \varepsilon_i^{t} \qquad (10)$$

Here equation (9) is the care seeking selection equation, while equation (10) is the expenditure equation conditional on care having being observed/sought~~-~~. Both equations include IMR as covariate to account for unobserved predictors of the insurance decision. These equations are estimated jointly using Heckman maximum likelihood estimation procedure.

## 4. RESULTS

This section starts by describing the raw data, comparing unadjusted mean differences in healthcare ~~cost~~expenditure between insured and uninsured groups by socioeconomic groups, before turning to the econometric results.

### 4.1 Descriptive statistics

The descriptive statistics for the variables of interest are presented in Appendix A1. Most respondents were residents of rural areas and 41% of them were farmers by profession. The insured made up 20.25% of the sick sample, and were likely to be more educated and in hired employment. Figure 1 summarises health care ~~cost~~expenditures as proportions of total household consumption expenditure. As one would expect, although richer quintile groups incurred higher ~~cost~~expenditures of care in absolute monetary terms, the proportion of income sacrificed was substantially lower than in the poorest quintile groups. The figure shows that the proportionate shares were consistently lower for the insured group.

*(Figure 1 about here)*

**4.2 Regression results**

The regression models used in this study estimate the impact of insurance membership on ~~the~~ healthcare ~~cost~~expenditure~~ of health care~~. The analysis was carried out using Stata version 12.1. The unit of analysis was an individual for whom the questionnaire was completed.

Table 1 presents the main results from the ~~cost~~expenditure models.

*(Table 1 about here)*

The OLS analysis was carried out on all individuals who reported illness over the past three months. The observed ~~cost~~expenditure for those who did not seek care was zero. The OLS model takes both zero and non-zero values as ~~cost~~expenditures, and does not explicitly model the care-seeking decision. The OLS model passed the Ramsey RESET test with test score $F(3, 1{,}164) = 0.32$ and $p > F = 0.81$, and had an R-squared value of 0.25. OLS results show a statistically significant negative effect of insurance membership on the log of health care ~~cost~~expenditure [Table 1]. After the transformation in equation (6), the OLS model estimates that insurance membership reduced OOP expenditures~~costs~~ by 51.3% (see figure 2). Regression results also show that the socioeconomic status of an individual is positively related to their observed healthcare ~~cost~~expenditure~~ of care~~, suggesting positive income elasticity which makes intuitive sense. ~~Cost~~Expenditure on~~f~~ health care was also observed to have a strong positive relationship with inpatient admissions and long-term health care status. Patients who self-assessed their health as fairly bad, or those who were suffering from long-term illness, incurred substantially higher ~~cost~~expenditure than those in good health.

The OLS model does not correct for potential care-seeking and insurance-seeking selection bias. Following Waters (1999) [49], we tested for the presence of care-seeking and insurance-seeking selection biases by separately introducing the predicted probabilities from the care-seeking and insurance-seeking probit models into the OLS model. Statistically significant coefficients (care-seeking: p = 0.02; insurance-seeking: p = 0.00) indicated the presence of selection biases.

Heckman's sample selection model (model 2) is employed to allow for care-seeking selection by joint estimation of ~~cost~~ healthcare expenditure ~~of care~~ and care-seeking equations. The coefficient on insurance in the Heckman model was much higher at -0.949 compared to -0.676 in the OLS model [Table 1], suggesting that the correlation between the residuals of the care-seeking probit and ~~cost~~ healthcare expenditure ~~of care~~ models should not be ignored. The *rho* parameter for independence of the care-seeking and ~~cost~~expenditure equations in the sample selection model was weakly significant (p = 0.06). After the transformation based on equation [6], the impact of insurance was estimated to be 63.1% (see figure 2). The coefficient on log of consumption expenditure also showed a small increase after correction for care-seeking bias. We also evaluated the coefficients in the care-seeking equation in the model that suggest that socioeconomic and insurance status does not significantly influence the decision to seek care [Table 2], although insurance significantly reduces the ~~cost~~ healthcare expenditure ~~of care~~ when treatment is sought.

Model 3 is the treatment effects model that accounts for the potential endogeneity of the insurance decision. This model has been commonly employed in the literature and aims to correct for insurance selection bias by independently identifying insurance-seeking decision whilst jointly estimating the ~~cost~~ healthcare expenditure ~~of care~~ model. However, the model ignores any potential care-seeking selection bias. The insurance-seeking equation was identified using instrumental variables that identify the insurance-seeking process. Following Waters (1999) [49], the appropriateness of the identifying variables was tested by introducing the identifying variables on the right hand side of a reduced form probit equation for the insurance-seeking decision. Statistically significant coefficients on identifying variables indicated that the variables were appropriate candidates. Subsequently, the identifying variables were included on the right hand side of the healthcare ~~cost~~expenditure ~~of care~~ model to establish that they did not significantly predict the ~~cost~~expenditure model.

The coefficient on the insurance variable in model 3 was -1.086, compared to -0.676 in the OLS model, suggesting that the OLS model had underestimated the impact of insurance membership on healthcare ~~cost~~expenditure ~~of care~~. Following equation [6], the impact of insurance on healthcare ~~the cost~~expenditure ~~of care~~ was estimated to be 69.0% (see figure 2). The *rho* parameter for independence of the insurance-seeking and ~~cost~~expenditure equations in the sample selection model was statistically significant (p = 0.01) indicating significant correlation between the residuals of the insurance-seeking probit and healthcare ~~cost~~expenditure ~~of care~~ models. We also evaluated the coefficients in the insurance-seeking equation in the model that suggest that years of schooling and rural residence were positively associated with insurance seeking decision, while female gender, wage employment and chronic illness were negatively associated with the insurance-seeking decision. The coefficients on identifying variables suggest that the insurance decision was indeed positively associated with medium to high level of worry about future health, membership of mass organisation and knowledge about the benefits of VHI and where to get the membership card.

Models 2 and 3 account for either care-seeking or insurance-seeking selection decisions but not both. Model 4 aims simultaneously to account for the two types of selection decisions by introducing the IMR term from the insurance probit (the first part of model 4) into the Heckman sample selection equations in the second part of the model (i.e. the healthcare ~~cost~~expenditure ~~of care~~ and care-seeking equations). IMR and its squared and cubic forms have different levels of statistical significance in the selection part of the model. Large values of the t-ratio associated with the IMR term suggest the presence of sample selection bias [50].

Results from model 4 show that the effect of IMR in the healthcare ~~cost~~expenditure ~~of care~~ model was positive and concave, suggesting that the unobservable factors associated with the insurance decision are associated with higher healthcare ~~cost~~expenditures ~~of care~~ but at a diminishing rate. In the care-seeking model, IMR was found to have a negative effect on the probability of seeking care. The Wald statistic for independence of the care-seeking and ~~cost~~ healthcare expenditure ~~of care~~ equations rejected the null-hypothesis of no correlation [p>z = 0.01]. Most importantly, the coefficient on insurance membership in model 4 was -1.238 compared to -0.676 in the OLS model, suggesting that the naïve model significantly underestimated the impact of insurance by ignoring selection biases. When the coefficient was transformed using equation [6], the magnitude of the impact was 72.3% compared to 51.3% estimated in the OLS model (see figure 2). This shows that not accounting for the selection biases underestimated the impact of voluntary insurance by 21 percentage points.

*(Figure 2 about here)*

## 5. DISCUSSION

This paper develops an approach to account simultaneously for insurance-seeking and care-seeking selection biases in modelling the impact of VHI on health care ~~cost~~expenditures. We illustrate these methods using survey data on the impact of a Vietnamese voluntary health insurance programme on individual out-of-pocket health care ~~cost~~expenditure~~s~~. The naïve OLS model suffers from important selection biases due to care-seeking and insurance-seeking decisions. This is because correlation between the ~~cost~~expenditure on ~~of~~ care and unobserved determinants of the care-seeking and insurance-seeking decisions is likely to produce biased estimates. Although previous studies have allowed for insurance-seeking selection bias, these studies have not allowed for simultaneous care-seeking selection. The contribution of this paper is to propose and illustrate a method for simultaneously allowing for both forms of selection bias. In our illustrative example, we use four different econometric models to compare the results of naive OLS against models allowing for each form of bias, both separately and jointly.

Results from the naïve OLS model suggest that insurance membership reduces out of pocket ~~cost~~expenditure by 51.3%. When both insurance-seeking and care-seeking decisions were taken into account, however, the impact of insurance on reducing health care ~~cost~~expenditures increased to 72.3%. Moreover, results also confirmed the presence of correlation between health care ~~cost~~expenditure and unobserved determinants of the selection decisions.

The relative magnitude of the impact of the two selection decisions on insurance coefficients in the ~~cost~~expenditure model will depend on the level of selection bias in a particular study. The care-seeking bias is important in the case of low-income countries with predominantly out-of-pocket healthcare systems where the decision to seek care is often correlated with the expected healthcare ~~cost~~expenditure. The impact of correcting for care-seeking bias is likely to be higher when insurance status is a strong predictor of the care-seeking decision, i.e. the insured have a higher probability of seeking care when ill. This was not found to be the case in the illustrated example of Vietnam, but ~~other~~ studies in other contexts have found that the insured are more likely to seek care when ill and to seek care from higher-level providers [18] which would result in higher ~~cost~~expenditures in the insured group.

We compared our results with Jowett et al (2003) [24] who used the same data but only corrected for insurance selection but ignored the care-seeking selection bias. The final coefficient of the impact of insurance on OOP expenditures~~costs~~ was higher in Jowett et al, i.e. -1.6 compared to our final estimate of -1.24. This is because they estimated the impact of insurance for individuals who sought care, and therefore benefitted more from insurance membership in terms of reduction in OOP expenditures~~costs~~. Therefore, the estimate from Jowett et al [24] is not generalisable to the wider population who need health care, and is also not directly comparable to our estimates.

Our illustrative analysis found that socioeconomic status had a positive and statistically significant relationship with out of pocket health care ~~cost~~expenditures. However, richer quintile groups were found to pay less as a percentage of their total consumption expenditure, consistent with the findings in other studies of Vietnam[51, 52]. This mirrors broader concerns about inequity in health care financing in low-income countries that have been extensively discussed in the literature [53] [30] [54].

The study also finds that insurance membership did not have a statistically significant impact on the probability of care-seeking, suggesting that other factors may play an important role in the care-seeking decision. One such factor may be geographical access to health services, since province of residence is associated with the care-seeking decision. 94.05% of the sick residents of Dong Thap sought care, compared to 66% and 86% of residents from Hai Phong and Ninh Binh provinces, respectively.

We also modelled the probability of health insurance uptake, which was found to be positively associated with the socioeconomic status of an individual. Richer individuals were more likely to purchase insurance, and in turn to benefit from ~~cost~~expenditure reduction. This is likely to have equity implications, especially if the insurance fund is subsidised through government funding.

Our study uses data on a relatively small health insurance programme targeting just three provinces of Vietnam to illustrate our method of accounting for double selection bias. However, the issue of double selection bias is also likely to occur in larger programme evaluations with broader populations. Indeed, one might anticipate that as programmes target and evaluate broader populations the insurance-seeking element of bias may reduce – because there is less scope for selection – whereas the care-seeking element of bias may increase.

This is because broader programmes are likely to include older, sicker and more disadvantaged populations who are likely to face greater care-seeking barriers. Moreover, selection biases also depend on the type of coverage and benefits of health insurance programme as well as the study context. For instance, while compulsory health insurance programmes are generally not affected by insurance-seeking adverse selection, they may still suffer from care-seeking selection issue. In case of Vietnam, Sepehri et al (2011) evaluated both compulsory health insurance (CHI) and voluntary health insurance (VHI) programmes and found that the impact of CHI on reducing OOP healthcare expenditure was higher than VHI. This may be partly because VHI is more likely to be influenced by adverse selection. Similarly, coverage (such as type of services and health facilities covered) and level of insurance co-payment may also the impact of insurance and the influence insurance-seeking and care-seeking selection biases.

In case of Vietnam, ~~Recently,~~ a number of ~~few~~ studies have used a ~~larger~~ national dataset from different waves of the Vietnam Household Living Standard Survey (VHLSS) to evaluate the impact of different types of health insurance programmes. Appendix table A3 summarises the methods and results of studies evaluating the impact of health insurance in Vietnam. These studies evaluate one or more of the following insurance programmes in Vietnam: (1) voluntary health insurance (VHI); (2) compulsory health insurance (CHI); (3) Vietnam Health Care Fund for the Poor (VHCFP); and (4) free healthcare for children under 6 years. These studies come to different conclusions which are summarised here. ~~have come to different conclusions using data from different waves of this survey: for instance,~~ Sepehri et al. (2006) [25] evaluated both VHI and CHI together using VHLSS for 1992-3 and 1997-8 and corrected for care-seeking bias using Tobit model (fixed and random effects) but not accounting for insurance endogeneity. They found that insurance reduce OOP expenditure~~costs~~ by 17% to 20%. Jowett et al (2003) used the same dataset as our study (i.e. survey of three provinces in year 1999), and corrected for insurance endogeneity but not care-seeking bias (and only used positive OOP expenditure observations). They found that VHI significantly reduced OOP expenditure, although their coefficients are much larger than ours results because they only used observations with positive OOP expenditures (therefore, their model results cannot be generalised to the wider population). Finally, Nguyen (2012) [6] evaluated the impact of VHI using VHLSS 2004 and 2006 using PSM and double differencing (i.e. difference-in-difference) to account for insurance selection and found that the effect of VHI on OOP expenditures is not statistically significant; however, they found that insurance increases the annual outpatient and inpatient visits by 45% and 70% respectively which partly explains no statistically significant reduction in OOP expenditure despite insurance reducing the price of care.

Wagstaff (2007) [55] evaluated VHCFP programme in Vietnam using VHLSS 2004 wave using propensity score matching (PSM) for insurance selection and found that it did not reduce the average out-of-pocket expenditure because it increased the probability and number of inpatient and outpatient visits. The same programme was evaluated by Axelson *et al* (2009) using PSM followed by double differencing for insurance endogeneity, and by Wagstaff (2010) using PSM followed by triple differencing to account for both observed and unobserved heterogeneity (see Appendix for details). Axelson *et al* (2009) found that VHCFP reduced only inpatient OOP but not overall expenditure, while Wagstaff (2010) found that VHCFP reduced both inpatient OOP and total OOP expenditures. Finally, Sepehri *et al* (2011) evaluated CHI, VHI and VHCFP using VHLSS waves 2004 and 2006 using fixed and random effects models and found that CHI and VHI reduced OOP expenditure at district hospitals by 40% and 32% respectively but did not reduce expenditure for those using commune health centres.

The above studies account for observables, and in most cases also unobservable, of the insurance-seeking decision (through PSM or regression with/without difference-in-difference methods). However, none of these studies simultaneously accounted for care-seeking and insurance-seeking biases which may partly explain some of these differences in findings ~~and Nguyen (2012) [6] found that the effect of insurance on OOP was not statistically significant. It is therefore perhaps unfortunate that recent studies using larger data in Vietnam have only adjusted for insurance-seeking bias and not also for care-seeking bias which may partly explain some of these differences~~ [56].

The focus of our study was on selection on unobservables, while also accounting for observable differences using regression model. As noted earlier, ~~We note that~~ selection on observables can be dealt with using different approaches, with regression and matching methods being the most popular in the literature. ~~The debate on regression versus matching to control for observables is not yet settled, with some authors concluding that the difference between estimates is not likely to be of major empirical significance [29]. The advantage of matching over regression is that it matches individuals based on their propensity to buy insurance by restricting the sample to observations that are comparable (at least in terms of~~

~~observed characteristics). Moreover, the matching methods make fewer assumptions about model specification. However, if the distribution of observed characteristics is similar in the insured and uninsured groups, and there is complete overlap between the two groups in terms of the range of propensity score (i.e. they have common support), then regression analysis will not rely on predicting expected outcomes based on observed characteristics beyond the ranges of observable characteristics in the insured and uninsured groups.~~ We found in our data that respondent characteristics were similar for most observed characteristics, and more importantly, the predicted propensity for insurance had complete overlap (i.e. common support). Based on this, the choice of method for dealing with observable difference is unlikely to be significant in this study. Moreover, neither regression nor matching account for selection on unobservables. Finally, our proposed approach for selection on unobservables can be easily applied to matching methods using weighted propensity score method.

There are also other econometric approaches available in the literature that account for selection on unobservables [57] [58]. At least one of them, i.e. the instrumental variable approach, has been shown to be equivalent to Heckman's sample selection model when selection decision is binary (which is the case in this study) [59]. Further research can explore if using other selection models produce similar results.

The modelling approach used in this study is relevant to non-randomised settings evaluating the effect on insurance on OOP expenditures. Randomised studies, such as the RAND health insurance experiment [60], which allocated individuals to different health insurance plans, are likely to have balanced groups in terms of their unobserved propensity to seek care (by virtue of randomisation). As a result, the average treatment effect can be estimated without the need to account for selection biases. However, most health insurance studies are not randomised, and therefore need to consider the issue of care seeking selection bias. Allowing for sample selection bias implies estimates can be generalised to individuals who did not seek care [61], which addresses the important question of 'What would have been the effects of health insurance had these individuals sought care?'.

The study has some limitations. Firstly, identification of the care-seeking equation relied on non-linearity of the inverse Mill's ratio. Whilst this is the common practice when instrumental variables are not available [50], the care-seeking decision may be better identified with unique instrumental variables. For the insurance-seeking selection, we used instrumental variables, though of course identification is only as good as the instrumental variables used. Secondly, Heckman's selection model assumes bivariate normality of error terms of the selection and outcome equations. The consequences of violation of this assumption should be explored in future work. Thirdly, whilst our proposed approach controls for the first hurdle, i.e. the care-seeking decision, it did not completely control for the quantity and quality of healthcare received. In a case study of China, Wagstaff and Lindelow (2008) [18] found that insurance encouraged individuals to seek care and to seek care from higher-level providers, which will have an effect of the estimation of true impact of insurance on OOP expenditure~~costs~~. Finally, insurance premiums were unknown for most respondents and, hence, were not included in the analysis. This means that all models will  over-estimate the impact of voluntary insurance; however, the overestimation is unlikely to be substantial, given the low level of premiums relative to average health ~~cost~~expenditures amongst the insured.

In conclusion, when access to health care is determined primarily by ability to pay, out-of-pocket payments are one of the most significant barriers to health care access, resulting in an inequitable distribution of health and health service utilisation [44] [62]. Hence, evaluation of the impact of VHI and other schemes on reducing out of pocket ~~cost~~expenditures is important, in order to find both ~~cost~~expenditure-effective and equitable ways of extending financial protection mechanisms to improve access to health care.  This study has developed a method for allowing simultaneously for both care-seeking and insurance-seeking selection biases, and has highlighted the significance of employing unbiased econometric models for estimating the impact of health insurance on the healthcare ~~cost~~expenditure~~ of care~~. In the context of low-income countries, where substantial numbers of individuals may be deterred from seeking care due to geographical and financial barriers to access, it is important to allow for care-seeking selection bias as well as insurance-seeking selection bias. Finally, our method can be generalised to evaluation of other types of health insurance programmes (such as social insurance) if they include an element of choice for the enrolment and care-seeking decisions that can be influenced by expected future healthcare ~~cost~~expenditures.

**Figure 1: OOP health care expenditure ~~cost~~ as percentage of total consumption expenditure**

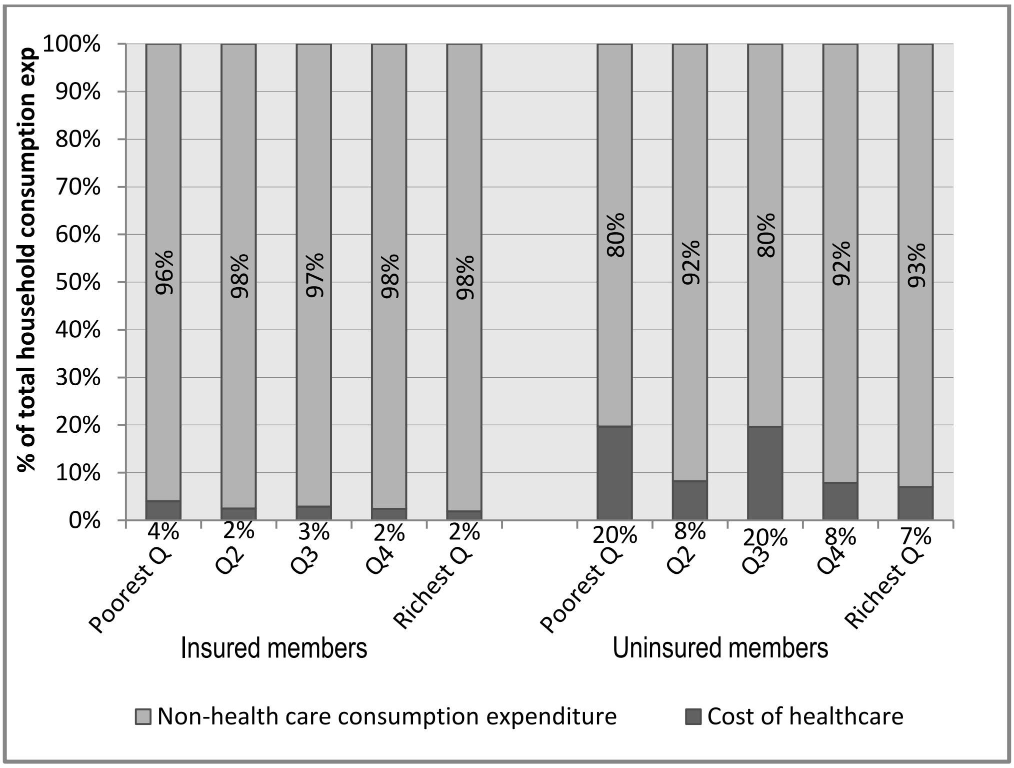

**Figure 2: Impact of insurance membership on out-of-pocket healthcare ~~cost~~expenditure ~~of care~~**

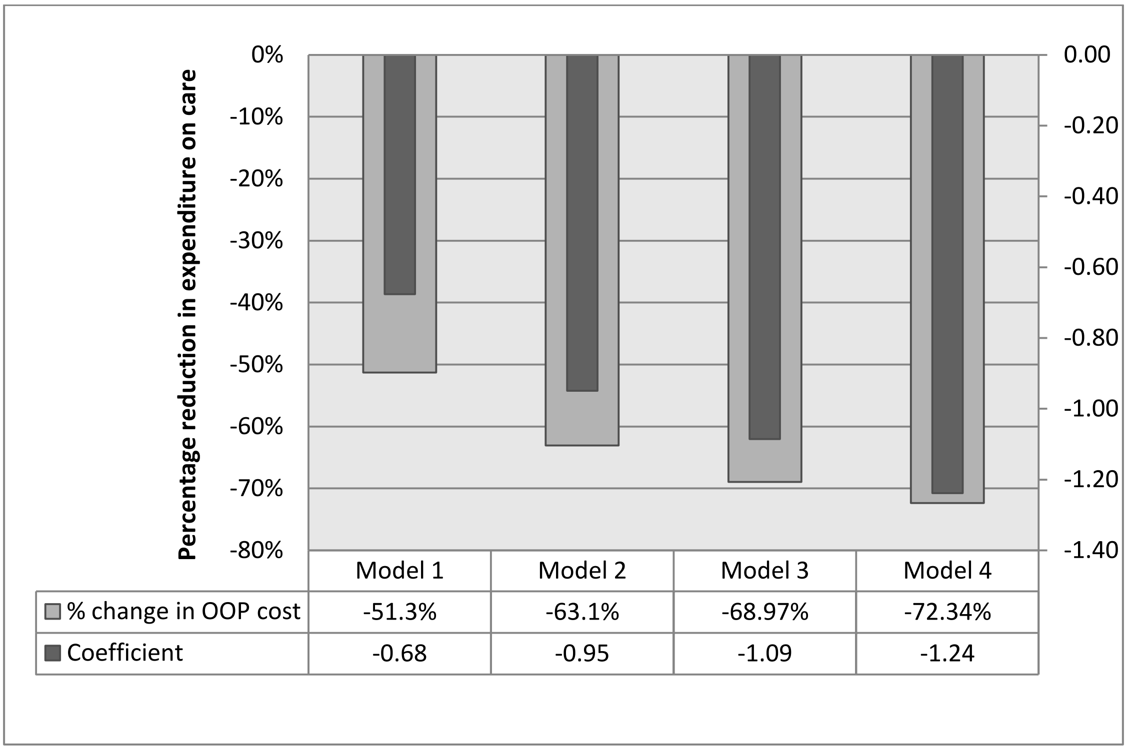

**Table 1: Results of econometric analysis of ~~Models of~~healthcare ~~the cost~~expenditure ~~of health care~~**

| **Dependent variable: Log of individual level healthcare ~~cost~~expenditure ~~of health care~~** | **Model 1: OLS** | **Model 2: sample selection model allowing for care-seeking selection** | **Model 3 - Treatment effects model allowing for insurance-selection** | **Model 4: Sample selection model allowing for both care-seeking and insurance-selection** |
|---|---|---|---|---|
| Member of VHI programme | -0.676** | -0.949*** | -1.086*** | -1.238*** |
| | (0.03) | (0.00) | (0.01) | (0.00) |
| Log of equivalent annual household expenditure | 0.419** | 0.459*** | 0.437** | 0.488*** |
| | (0.03) | (0.00) | (0.01) | (0.00) |
| Age | 0.008 | 0.006 | 0.006 | 0.002 |
| | (0.65) | (0.71) | (0.75) | (0.90) |
| Age-squared | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.76) | (0.66) | (0.87) | (0.82) |
| Female | 0.041 | -0.184 | 0.033 | -0.193 |
| | (0.91) | (0.51) | (0.93) | (0.51) |
| Interaction between age and sex | 0.004 | 0.010 | 0.005 | 0.010 |
| | (0.59) | (0.14) | (0.56) | (0.13) |
| No. of illnesses in last 3 months | -0.028 | 0.010 | -0.029 | 0.010 |
| | (0.65) | (0.84) | (0.63) | (0.83) |
| Inpatient admission in last 3 months | 2.332*** | 2.488*** | 2.320*** | 2.467*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Health status: fairly good | 0.061 | -0.201 | 0.031 | -0.243 |
| | (0.82) | (0.46) | (0.91) | (0.39) |
| Health status: fairly bad | 0.800** | 0.721*** | 0.796*** | 0.700** |
| | (0.02) | (0.01) | (0.01) | (0.01) |
| Health status: long-term Illness | 0.909** | 0.698* | 0.906** | 0.675* |
| | (0.03) | (0.06) | (0.02) | (0.07) |
| Chronic illness | 0.099 | 0.103 | 0.077 | 0.076 |
| | (0.76) | (0.72) | (0.80) | (0.78) |
| Rural residence | 0.304 | 0.317 | 0.316* | 0.332* |
| | (0.12) | (0.12) | (0.09) | (0.10) |
| Province: Hai Phong | -0.524 | -0.008 | -0.549 | -0.004 |
| | (0.23) | (0.99) | (0.20) | (0.99) |
| Province: Ninh Binh | 0.011 | 0.144 | -0.017 | 0.115 |
| | (0.96) | (0.62) | (0.93) | (0.68) |

| | | | | |
|---|---|---|---|---|
| Occupation: service | 0.270 | 0.385** | 0.250 | 0.350* |
| | (0.28) | (0.03) | (0.31) | (0.05) |
| Occupation: farmer | 0.021 | -0.040 | -0.004 | -0.077 |
| | (0.90) | (0.85) | (0.98) | (0.72) |
| Occupation: wage | -0.166 | -0.252 | -0.185 | -0.284 |
| employment | (0.31) | (0.18) | (0.24) | (0.14) |
| Years of schooling | -0.022 | -0.010 | -0.014 | -0.002 |
| | (0.53) | (0.75) | (0.67) | (0.96) |
| Interaction between | 0.001 | -0.008 | 0.002 | -0.008 |
| schooling and gender | (0.96) | (0.71) | (0.95) | (0.74) |
| Interaction between | 0.001 | 0.001 | 0.000 | 0.001 |
| schooling and age | (0.50) | (0.30) | (0.55) | (0.34) |
| Inverse Mills' Ratio | - | - | - | 0.471* |
| | - | - | - | (0.08) |
| Inverse Mills' Ratio – | - | - | - | -0.236*** |
| squared | - | - | - | (0.00) |
| Inverse Mills' Ratio - cube- | - | - | - | 0.018 |
| root | - | - | - | (0.48) |
| Constant | -0.635 | -0.791 | -0.701 | -0.892 |
| | (0.66) | (0.51) | (0.62) | (0.45) |
| Rho | - | 1.269* | 0.224** | 1.197* |
| | - | (0.06) | (0.01) | (0.05) |
| Sigma | - | 0.406*** | 0.479*** | 0.398*** |
| | - | (0.00) | (0.00) | (0.00) |
| Observations | 1189 | 1189 | 1189 | 1189 |
| R-squared | 0.26 | - | - | - |

Robust p values in parentheses *** p<0.01, ** p<0.05, * p<0.1

**Table 2: Intermediate probit models of care-seeking and insurance-seeking decisions**

| Covariates: | Care-seeking model (part of model 2) | Care-seeking model with correction for insurance-selection (part of model 4) | Insurance-seeking model (part of model 3) |
|---|---|---|---|
| Member of VHI programme | -0.254 | 0.317 | - |
| | (0.33) | (0.50) | - |
| Log of equivalent annual household expenditure | 0.185 | 0.190 | 0.355* |
| | (0.31) | (0.33) | (0.10) |
| Age | -0.015 | -0.013 | -0.265*** |
| | (0.64) | (0.68) | (0.00) |
| Age-squared | 0.000 | 0.000 | 0.002*** |
| | (0.60) | (0.64) | (0.00) |
| Female | 0.259 | 0.302 | -1.333*** |
| | (0.70) | (0.67) | (0.00) |
| Interaction between age and sex | -0.001 | -0.001 | 0.048** |
| | (0.94) | (0.92) | (0.03) |
| No. of illnesses in last 3 months | -0.092 | -0.088* | - |
| | (0.10) | (0.09) | - |
| Health status: fairly good | 0.416 | 0.464* | -0.525** |
| | (0.15) | (0.08) | (0.02) |
| Health status: fairly bad | 0.334 | 0.351 | 0.679* |
| | (0.29) | (0.23) | (0.07) |
| Health status: long-term Illness | 0.682 | 0.716 | 0.590 |
| | (0.29) | (0.23) | (0.44) |
| Chronic illness | -0.003 | -0.009 | -1.720*** |
| | (0.99) | (0.98) | (0.00) |
| Rural residence | 0.078 | 0.074 | 0.988* |
| | (0.75) | (0.75) | (0.08) |
| Province: Hai Phong | -1.196*** | -1.171*** | -2.117*** |
| | (0.00) | (0.00) | (0.00) |
| Province: Ninh Binh | -0.551* | -0.531** | -2.080*** |
| | (0.05) | (0.04) | (0.00) |
| Occupation: service | 0.039 | 0.035 | -0.838* |
| | (0.92) | (0.93) | (0.07) |
| Occupation: farmer | 0.224 | 0.241 | -0.345 |
| | (0.45) | (0.42) | (0.58) |

| | | | |
|---|---|---|---|
| Occupation: wage employment | 1.463 | 1.539* | -1.213** |
| | (0.11) | (0.05) | (0.05) |
| Years of schooling | -0.033 | -0.037 | 0.166*** |
| | (0.59) | (0.58) | (0.00) |
| Interaction between schooling | 0.012 | 0.010 | 0.029 |
| and gender | (0.83) | (0.85) | (0.74) |
| Interaction between schooling | 0.000 | 0.000 | 0.007*** |
| and age | (0.78) | (0.77) | (0.01) |
| Respondent has medium to high level of worry about future | - | - | 1.888*** |
| health | - | - | (0.00) |
| Member of a mass organisation | - | - | 0.909*** |
| | - | - | (0.00) |
| Do you know where to go get hi | - | - | 2.432*** |
| card? | - | - | (0.00) |
| Do you think or know of any benefit of VHI when getting | - | - | 0.597*** |
| medicines? | - | - | (0.01) |
| Inverse Mills' Ratio | - | -0.221 | - |
| | - | (0.57) | - |
| Inverse Mills' Ratio – squared | - | -0.244** | - |
| | - | (0.02) | - |
| Inverse Mills' Ratio - cube-root | - | 0.047* | - |
| | - | (0.09) | - |
| Constant | 0.270 | 0.142 | -4.885*** |
| | (0.86) | (0.93) | (0.00) |
| Observations | 1189 | 1189 | 1189 |

Robust p values in parentheses *** p<0.01, ** p<0.05, * p<0.1

## Appendices

### Table A1: Descriptive statistics for the variables of interest

| Variable Name | Respondents reporting sickness in the last 3 months (N=1,192) Mean | Sick respondents who sought health care (N=982) Mean | Insured who were also sick (N=242) Mean | Uninsured who were also sick (N=950) Mean |
|---|---|---|---|---|
| Member of Voluntary Health Insurance (percentage of respondents) | 20.25 | 17.09 | - | - |
| Age (years) | 35.86 | 35.95 | 34.80 | 32.42 |
| Female (percentage of respondents) | 55.75 | 56.70 | 38.59 | 56.38 |
| Rural resident (percentage of respondents) | 81.81 | 82.22 | 72.20 | 71.65 |
| Resident of Hai Phong (percentage of respondents) | 8.32 | 6.43 | 31.95 | 7.17 |
| Resident of Ninh Binh (percentage of respondents) | 28.33 | 27.67 | 4.98 | 48.89 |
| Resident of Dong Thap (percentage of respondents) | 63.35 | 65.90 | 63.07 | 43.94 |
| Occupation – service/business (percentage of respondents) | 11.55 | 11.28 | 8.71 | 10.33 |
| Occupation – farmer (percentage of respondents) | 41.28 | 41.12 | 25.31 | 29.82 |
| Occupation - hired (percentage of respondents) | 6.80 | 7.38 | 8.30 | 5.48 |
| Occupation – student (percentage of respondents) | 22.32 | 21.18 | 22.82 | 35.83 |
| Occupation – retired (percentage of respondents) | 7.68 | 7.36 | 2.90 | 6.74 |
| Occupation - other (percentage of respondents) | 10.37 | 11.68 | 3.32 | 12.96 |
| Number of years of schooling | 5.32 | 5.18 | 8.19 | 6.03 |
| Health status - good (percentage of respondents) | 20.27 | 18.64 | 37.76 | 21.29 |

| | | | | |
|---|---|---|---|---|
| Health status - fairly good (percentage of respondents) | 51.54 | 52.66 | 37.34 | 52.90 |
| Health status - fairly bad (percentage of respondents) | 16.21 | 16.33 | 14.11 | 11.70 |
| Health status - long-term illness (percentage of respondents) | 11.99 | 12.37 | 10.79 | 14.12 |
| Chronic illness (percentage of respondents) | 14.78 | 15.16 | 12.45 | 13.28 |
| Number of illnesses in the last 3 months | 2.01 | 2.02 | 2.08 | 1.88 |
| Inpatient care (yes) (percentage of respondents) | 10.19 | 9.82 | 13.25 | 9.20 |

Table A2: Average health care ~~cost~~expenditures per person in the last three months (by consumption quintiles)

| | **Poorest quintile (‘000 VND) (N = 239)** | **Quintile 2 (‘000 VND) (N = 238)** | **Quintile 3 (‘000 VND) (N = 238)** | **Quintile 4 (‘000 VND) (N = 240)** | **Richest quintile (‘000 VND) (N = 236)** | **Total (‘000 VND) (N = 1,192)** |
|---|---|---|---|---|---|---|
| Insured | 29.85 | 29.86 | 45.87 | 52.95 | 98.99 | 66.69 |
| Uninsured | 176.40 | 101.29 | 356.28 | 159.15 | 283.30 | 212.76 |
| Average | 174.758 | 98.418 | 322.697 | 170.794 | 268.020 | 206.091 |

**Table A3:** Summary of published studies evaluating the impact of health insurance in Vietnam

| **Study** | **Data** | **Type of analysis** | **Results** |
|---|---|---|---|
| Jowett *et al* (2003) | Single cross-sectional survey conducted in year 1999 using purposive sampling to evaluate the voluntary component of Vietnam's voluntary health insurance (VHI) programme – before the introduction of Vietnam Health Care Fund for the Poor (VHCFP). Survey conducted in 3 provinces (Ninh Binh, Hai Phong and Dong Thap). This data is the same as used in our paper. | Heckman's two-step regression was used to correct for insurance endogeneity. First step was a probit regression for probability of insurance. Inverse Mills Ratio (IMR) was obtained from this model and included in the OLS regression for out-of-pocket (OOP) expenditure. The expenditure equation included only non-zero values for health expenditure; hence, care-seeking selection was ignored. | Overall, health insurance was found to reduce average out-of-pocket expenditures. The dependent variable was the log of out-of-pocket expenditure. The coefficient on insurance was -2.080 (p=0.001) after correcting for insurance endogeneity which was interpreted incorrectly as 200% reduction in expenditure. |
| Sepehri *et al* (2006) | National data from 1992-3 and 1997-8 waves of the Vietnam Living Standards Survey (VLSS) to evaluate Vietnam's health insurance programme; however, unlike Jowett *et al* (2003), both compulsory (predominant) and voluntary health insurance was included and jointly evaluated because VLSS did not provide distinction between the two types. | Two approaches were used with panel individual effect: (1) Tobit model which treats zero expenditure as censored (i.e. censored value for selecting into care, not insurance); and (2) truncated regression which uses only positive expenditure. Fixed and random effects models were used.<br><br>Insurance endogeneity bias was not taken into account, partly because both compulsory and voluntary insurance was included. | Random and fixed effects models produce different results. Final set of results show that health insurance reduces out-of-pocket health expenditure (between 17 and 20%). |
| Wagstaff (2007) | National data from VHLSS 2004. The study evaluated VHCFP which was introduced in 2003. | Propensity score matching was used to account for insurance endogeneity, followed by regression weighted by propensity score weights. | Total out-of-pocket health expenditure is reduced by VHCFP in the simple PSM but not with the regression. The study concluded that VHCFP did not reduce average out-of-pocket expenditure because it increased the probability and number of inpatient and outpatient visits. A secondary finding was that VHCFP reduced the risk of catastrophic spending by 3-4%. |

| **Study** | **Data** | **Type of analysis** | **Results** |
|---|---|---|---|
| Axelson *et al* (2009) | VHLSS data from 2002 (pre-VHCFP) and 2004 (post-VHCFP) | First analysis used PSM for selection into insurance followed by single differencing (i.e. difference in OOP expenditure between insured and uninsured at one time point) in a cross-section analysis of VHLSS 2004. Second analysis used PSM followed by double differencing (or difference-in-difference, i.e. first calculating the mean difference in outcome before and after the intervention for the insured and uninsured groups separately, followed by calculating the difference between the mean differences of the two groups). This is done using panel dataset for VHLSS 2002 and 2004; the double differencing is to take account of time-invariant unobserved factors. | The result from the double differencing differs from single-differencing. Single differencing found statistically significant reduction in OOP expenditure at household level by 19% (although reduction in per capita expenditure of 14% was not significant). Results of difference-in-difference also found reduction in health care expenditure but they were only significant for inpatient care expenditure (absolute reduction of 134.6 Vietnamese Dong). |
| Wagstaff (2010) | VHLSS data from the panel element of the 2002, 2004 and 2006 waves. | Triple-differencing which involves difference-in-difference over three periods, i.e. besides the double difference-in-difference between insured and uninsured (as above), a further difference is taken to 'net out' the difference between the same groups in the change in mean OOP expenditure over an earlier period. Instead of assuming parallel trends in the unobservables for the insured and uninsured groups, it assumes that the change in unobservables for each group in the two periods (2002-2004) and (2004-2006) is the same. This method can be used with regression or matching to control for observables. The proposed method estimates programme impact on those covered by it but not | Single-difference with matching found no significant impact of VHCFP on out-of-pocket expenditure. Double and triple-differencing found significant negative impact on total OOP expenditure (-181 and -327 VND respectively) and OOP expenditure on inpatient care (-131 and -248 VND respectively). |

| **Study** | **Data** | **Type of analysis** | **Results** |
|---|---|---|---|
| | | those currently not covered. | |
| Sepehri *et al* (2011) | VHLSS data from the panel element of the 2004 and 2006 waves. The focus is on compulsory health insurance (CHI), VHI and insurance for the poor. | Fixed and random effects models were used. Fixed effects analysis was intended to control for time-invariant unobserved individual effects. Endogeneity bias due to adverse selection into insurance was not taken into account. | Random effects analysis showed that CHI and VHI reduce OOP expenditure by about 24% while health insurance for the poor reduces it by 15%. However, in the fixed effects analysis, the coefficients for CHI and VHI were not significant. Further analysis showed that CHI and VHI reduce OOP expenditures by 40 and 32%, respectively for those using district hospitals but not significant for commune centres. |
| Nguyen (2012) | VHLSS data from the panel element of the 2004 and 2006 waves. The focus is on voluntary health insurance. | PSM followed by double differencing (i.e. difference-in-difference). | The effect of voluntary health insurance on out-of-pocket expenditure on health care services is not statistically significant; however, insurance increases the annual outpatient and inpatient visits by 45% and 70% respectively which partly explains no statistically significant reduction in OOP expenditure despite insurance reducing the price of care. |
| Nguyen and Wang (2013) | VHLSS data from the panel element of the 2004 and 2006 waves. The focus was on evaluating a government policy to provide free healthcare for children younger than 6 years. The policy came into effect in the beginning of 2005. | Difference-in-difference approach using VHLSS wave 2004 (pre-policy) and 2006 (post-policy) in a regression model controlling for potential confounders. | Free health insurance reduced OOP health expenditure by US$5.09 in the age group 4-7. It also reduced the probability of having catastrophic OOP expenditure by 1.7 percentage point. |

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**TITLE PAGE**

| | |
|---|---|
| **Title of the paper** | Addressing care-seeking as well as insurance-seeking selection biases in estimating the impact of health insurance on out-of-pocket expenditure |
| **Running head** | Addressing care-seeking as well as insurance-seeking selection biases |
| **Tables** | 2 |
| **Figures** | 2 |
| **Appendix tables** | 3 |
| **Conflict of interest** | None |

**ABSTRACT**

Health Insurance (HI) programmes in low-income countries aim to reduce the burden of individual out-of-pocket (OOP) health care expenditure. However, if the decisions to purchase insurance and to seek care when ill are correlated with the expected healthcare expenditure, the use of naïve models may produce biased estimates of the impact of insurance membership on OOP expenditure. Whilst many studies in the literature have accounted for the endogeneity of the insurance decision, the potential selection bias due to the care-seeking decision has not been taken into account. We extend the Heckman selection model to account simultaneously for both care-seeking and insurance-seeking selection biases in the healthcare expenditure regression model. The proposed model is illustrated in the context of a Vietnamese HI programme and results compared with those of alternative models making no or partial allowance for selection bias. In this illustrative example, the impact of insurance membership on reducing OOP expenditures was underestimated by 21 percentage points when selection biases were not taken into account. We believe this is an important methodological contribution that will be relevant to future empirical work.

**Key words:** Health insurance; selection bias; endogeneity; Heckman model; low-income countries

# 1. INTRODUCTION

Out of pocket (OOP) payment is the predominant mechanism of health care financing in most low-income countries, accounting for over half of the total expenditure on health in low income countries [1]. These payments create financial barriers to health care access, especially for the poor, often resulting in long delays in seeking care until disease severity has progressed so far that much prolonged and expensive treatment is required [2]. Van Doorslaer et al (2007) [3] found that, among Asian countries, reliance on OOP payments was highest in Vietnam and India, where >80% of total health expenditures were funded by OOP expenditures. In the same study, Vietnam also had the highest proportion of individuals incurring catastrophic payments; this was reported to be 34%, 15% and 8.5% at threshold levels of 5%, 10% and 15% of total household expenditure.

In recent decades, many low-income countries have embarked on voluntary health insurance (VHI) programmes commonly characterised as not-for-profit, voluntary membership schemes with affordable, community-rated premia for all individuals. They may be organised at local or regional levels, like SEWA and ACCORD in India [4] and Grameen in Bangladesh [5], or at national level, like in Vietnam [6], Ghana [7] and Mexico [8]. The overarching aim of VHI programmes is to reduce the burden of out-of-pocket expenditures, and in turn provide financial protection to the target population. Based on the same principle, recent policy focus has been on providing universal health coverage (UHC) which entitles all people to access health care funded through publicly organised risk pooling [9]. Most high income countries already have some form of UHC while many middle and low-income countries (LMIC) are making significant progress in this direction [10] [11]. However, coverage in most LMICs is far from universal, both in terms of enrolment rates and the level of financial protection [11]. Moreover, use of care among the enrolled is often restricted by geographical access and co-payment contributions, resulting in forgone necessary care [12].

Several studies in recent years have focused on monitoring progress and evaluating effectiveness of various forms of risk pooling in providing financial protection (note: from hereon we will use the generic term ‘health insurance’ for all forms of risk pooling). While most studies found a positive effect of health insurance on reducing OOP expenditures [13] [8] [14] [15] [16] [17], some studies found mixed, negative or no significant effect [18] [19] [20]. Systematic reviews focusing on performance of health insurance have found positive, mixed or inconclusive evidence on financial protection [21] [22] [23].

To measure the impact of health financing programmes on OOP, robust and consistent methods are required. The available evidence on the impact of insurance on OOP expenditures may have limitations due to differences in quantitative methodologies employed in evaluation studies. It has been noted in the literature that when the analysis is based on observed OOP expenditure, it may be biased due to individual-level selection decisions that influence the level of incurred expenditure[24] [25] [26]. Two selection decisions are particularly important in the context of evaluating the impact of health insurance on OOP expenditures in low-income countries. These are insurance-seeking and care-seeking selection decisions. Both decisions are determined by observable and unobservable characteristics that may also be correlated with expenditure on health care. It is now common for studies of the impact of VHI on OOP expenditure to allow for insurance-seeking bias due to adverse selection (based on both observable and unobservable characteristics). However, previous studies have not allowed for care-seeking selection bias. This study is innovative in allowing simultaneously for these two potential sources of bias. Our study extends the selection models to simultaneously correct for selection bias due to insurance-seeking as well as care-seeking decisions. The aim of this study is to illustrate this approach to estimate the impact of health insurance on OOP expenditure using observational data. We compare the results with those of alternative models that allow for selection biases only partially or not at all. For the purpose of illustration, this study uses data from a cross-sectional household survey of three provinces of Vietnam, conducted during the year 1999. However, the focus of this study is methodological.

The remaining paper is organised as follows. Section 2 discusses how care-seeking and insurance-seeking selection decisions may potentially bias OOP health care expenditure analysis. This is followed by some brief background on the Vietnamese voluntary health insurance programme, to help put the empirical results into context. Section 3 discusses the data and the econometric models employed in this analysis. Section 4 presents the results of econometric analysis, and finally, section 5 discusses the implications of the study findings.

## 2. SELECTION BIASES IN MEASURING THE IMPACT OF VHI

When selection decisions are correlated with the OOP expenditure of health care due to observable or unobservable characteristics, as discussed in detail below, the estimate of the impact of health insurance on OOP expenditure of care may be biased [27]. One potential source of bias is insurance selection. For example, individuals may be more likely to purchase insurance if they expect high future healthcare expenditures, i.e. voluntary insurance may be prone to adverse selection. This is also relevant to health financing programmes that are moving in the direction of universal health coverage; these programmes often include an element of choice for the enrolment decision which can be influenced by expected future healthcare expenditures. If so, then the insured may have greater health care needs and in turn higher expenditure than the uninsured, even after allowing for observed characteristics such as age, sex and self-reported health. In this case, the mean difference in OOP expenditure between insured and uninsured groups will under-estimate the causal impact of VHI on reducing OOP health care expenditure.

A second source of selection bias is attributable to the care-seeking decision. When an individual is sick and in need of health care, they make a decision to seek care or not, i.e. they face the care-seeking decision hurdle. For example, individuals may be less likely to seek care if they expect the expenditures to be high relative to the benefits, given their household financial situation. This in turn influences whether or not their health care expenditure is observed. If the care-seeking decision is correlated with health care expenditures, then not accounting for the care-seeking selection in healthcare expenditure model may bias the estimates. Moreover, the factors associated with the care seeking decision may be associated with the insurance decision.

Selection bias may occur due to observable or unobservable characteristics (i.e. confounders) that are also correlated with the outcome of interest. Selection on observables, such as age and gender, can be solved by using regression or matching methods [28]. These are commonly known as “control strategies” as they control for difference in characteristics between those who self-selected and those who did not, to allow causal inference [29]. However, regression and matching methods do not account for selection on unobservable factors that may be correlated with health care expenditures. It is this selection on unobservables which is the focus of this paper. For this, the common approaches include instrumental variables, control functions and the joint estimation of outcome and selection in a structural approach [27].

While some studies in the literature have acknowledged but not accounted for potential biases due to unobservable characteristics [26, 30], others have corrected for insurance selection only and not for care-seeking selection [25] [24] [18] [31]. We start with a more detailed discussion of the possible causes and impact of the two forms of selection bias.

### 2.1. Care-seeking selection and its impact on OOP expenditure

Care-seeking selection bias is a form of sample selection bias that occurs when the outcome of interest (in this case, the health care expenditure) is only observed for a sub-sample of the population that meets some criterion defined with respect to a selection decision (in this case, the care-seeking decision), and this selection decision is in turn associated with the outcome of interest [32] [33]. Hence, in the case of health care expenditure analysis, only a subsample of the sick population may seek care and in turn incur health care expenditures. If the care-seeking decision is not random but is associated with the expected healthcare expenditure, then we have selection problem. However, if all determinants of care-seeking decision (that are correlated with the outcome) are observed and included in the outcome (OOP expenditure) regression, then we have accounted for this selection bias. On the other hand, if the decision to seek care is correlated with OOP expenditure through unobserved factors, then the estimated coefficients in the expenditure model (including the coefficient on insurance membership), based on observed expenditure, may be biased. Not accounting for this selection will result in coefficient estimation based on a non-random sample. As a result, the observed effect of insurance on OOP expenditure will not be generalisable to the population who did not seek care. Therefore, to evaluate the policy impact of expanding insurance coverage (and hence access to care) to the entire population, it is important to account for selection bias induced by care seeking.

For example, an individual's degree of risk aversion with respect to health outcomes may be an unobserved factor associated with a higher probability of seeking care given illness and also with lower expenditure when care is sought. To put this the other way around, the subsample of individuals who seek care and have positive expenditures may be more risk averse and face relatively low expenditures of care. Hence, if risk attitude is not taken into account, health care expenditure may be under-estimated when extrapolating estimates of effects to the wider population of potential health care users. Secondly, because insurance reduces the price of health care and therefore increases the demand for health care, the insured may be more likely to seek care and in turn have their positive health care expenditures observed. If so, then the expenditure analysis will under-estimate the impact of expanding VHI to the wider population, on reducing OOP healthcare expenditures when care is sought. Wagstaff and Lindelow (2008) [18] found evidence of this during analysis of three household surveys in China. They found that after controlling for insurance-seeking bias, insurance membership was associated with an increased risk of high healthcare spending. They concluded that this is because insurance increased the probability of seeking care when ill which resulted in higher expenditures in the insured group; therefore, an evaluation of the impact of voluntary insurance should take account of care-seeking behaviour.

In a systematic review of insurance studies in developing countries, Acharya et al (2012) [21] found that care-seeking selection is not commonly addressed in the literature. Most studies ignore this by either using only the positive expenditure in the analysis [24], or treating zero and non-zero expenditures on the same scale without addressing the selection issue. Other insurance studies take a two-part modelling approach, separating the probability of seeking care from health care expenditure (conditional on seeking care). The following approaches have been used in the insurance literature in developing countries [21]: Tobit model, two-part models and selection models. These models include the care-seeking decision in the first part followed by health expenditure equation in the second part.

There is a strong case for separating the probability of seeking care from health care expenditure to assess the extensive margin i.e. decisions to seek care and impact on demand for contact with the health care service, which relies mainly on individual circumstances or preferences, degree of insurance coverage and access to health care services. This is then followed by evaluating the intensive margin which is primarily an agency relationship where treatment decisions are made by the treating physician, and influenced by the organisation, quality, prices and incentives in the health care system.

Separating out the contributions of health insurance in extensive and intensive margins on out-of-pocket expenditures is important. For instance, total OOP expenditure could increase if the extensive margin (threshold for seeking care) decreases, as greater frequency of treatment increases total expenditure. However, the impact of decreasing threshold on OOP expenditure once care is sought could also be negative if, for instance, more timely care due to lower threshold for care seeking impacts severity of illness when care is sought and treatment needs (due to more timely intervention). On the other hand, having insurance could affect treatment decisions of the physician and patients, i.e. prescription of more intensive and/or expensive treatments or the patient is exposed to risk of supplier induced demand (as observed in case of China [18]). Therefore, it is important to explore the influence of these different factors on health care expenditures, which the selection model intrinsically enables by estimating the propensity to seek care and indicating how this impacts expenditures once care is sought.

To understand all this mathematically, let the health care expenditure model be expressed as:

$$Expenditure_i = \alpha + \beta_1(Insurance)_i + \beta_x X_i + \varepsilon_i^Y \qquad (1)$$

Here $X$ is a vector of observed variables and $\varepsilon_i^Y$ represents the unobserved predictors of expenditure. Expenditure is only observed to be positive if an individual seeks health care, i.e. expenditure depends on an endogenous care-seeking decision ($CS_i$) such that:

$$Expenditure_i \begin{cases} = \ +ve \ \ if\ Care - seeking = Yes \\ \ = 0 \ \ if\ Care - seeking = No \end{cases} \qquad (2)$$

The probability of care-seeking, in turn, can be estimated as a probit model (3):

$$\Pr[Care - seeking] = \ \Phi(\beta_z Z_i + \ \varepsilon_i^{cs}) \qquad (3)$$

Here $\Phi$ represents the distribution of probit model and $Z$ represents the observed predictors of care-seeking decision, including insurance status. Expenditure is positive if latent propensity ($\beta_z Z_i$) to seek care exceeds the unobserved threshold for an individual.

If the unobserved predictors in the error terms of equations (1) and (3) are not independent of each other, then it implies that the observed expenditure on health care (and the estimated coefficients in expenditure regression) depends on the care-seeking process. This endogenous dependence of the error term violates one of the fundamental assumptions of least squares regression and gives rise to sample selection bias. Heckman (1977) [34] explains that this selection bias stems from the common problem of omitted variable bias, i.e. a situation whereby the model is missing one or more important predictors that are correlated with the selection decision as well as the outcome equation. The presence of omitted variable bias is then compensated by over- or under-estimating the coefficients of the observed factors in the model, such as the insurance variable in this case. As a result, estimated effects on the impacts of health insurance on OOP expenditures are unlikely to be generalisable to the wider population who were not observed to incur OOP expenditure.

### 2.2. Insurance-seeking selection

Voluntary health insurance programmes often attract sicker or more risk-averse individuals, i.e. insurance-purchase/participation decision is not randomly distributed in the population.

While regression analysis can control for age, sex and other observed factors, it cannot allow for unobserved aspects of the individual's health, preferences and environment that influence both health care expenditures and the insurance-purchase/participation decision. Insurance status may influence both the care-seeking decision and the healthcare expenditure. If part of this influence occurs through the unobserved determinants of the insurance-purchase/participation decision that are correlated with healthcare expenditure equation, then insurance status is not exogenous to the model. This would violate the classical exogeneity assumption of linear regression, and the model would suffer from endogeneity bias.

A number of approaches have been used in the literature to adjust for selection bias due to insurance-purchase/participation decision. These methods can be classified based on whether they deal with selection on observable covariates (or simply observables) or unobservable covariates (or unobservables) [27]. Selection on observables is commonly addressed using regression analysis or propensity score matching [21]. The debate on regression versus matching to control for observables is not yet settled, with some authors concluding that the difference between estimates is not likely to be of major empirical significance [29]. The advantage of matching over regression is that it matches individuals based on their propensity to buy insurance by restricting the sample to observations that are comparable (at least in terms of observed characteristics). Moreover, matching methods make fewer assumptions about model specification. However, if the distribution of observed characteristics is similar in the insured and uninsured groups, and there is complete overlap between the two groups in terms of the range of propensity scores (i.e. they have common support), then regression analysis will not rely on predicting expected outcomes based on observed characteristics beyond the ranges of observable characteristics in the insured and uninsured groups, and will give similar results to regression analysis.

For selection on unobservables of insurance-seeking decision, a number of methods exist in the literature. These include structural models and control functions; instrumental variables; regression discontinuity; and difference-in-difference [27]. Structural models involve specifying a model to determine treatment assignment and then jointly estimating this model with the outcome (i.e. OOP expenditure). Control function approach involves separately estimating the outcome equation, and capturing insurance selection bias by including a control term (known as Inverse Mills' Ratio, explained later) from a probit model for insurance selection [34]. This approach was taken by Jowett et al (2003) [24]. Instrumental variable approach is based on finding one or more variables that predict treatment (insurance) assignment but are not directly correlated with the outcome (OOP expenditure). This approach has been used by a number of studies, including Wagstaff and Lindelow (2008) [18]. Regression discontinuity design is used when assignment to treatment changes discontinuously with respect to some threshold value which determines whether someone is in the treated (insured) or untreated (uninsured) group. This approach was used by Bauhoff et al (2011) [35] and Miller et al (2009) [36]. Difference-in-difference approach (or double differencing) involves taking the difference in outcome (i.e. OOP expenditure) between insured and uninsured groups before and after the introduction of insurance and then taking the difference in these differences. This approach requires data in both pre-treatment and post-treatment periods and can be used with longitudinal/panel data or with multiple cross-sections [37] [38]). This approach has been commonly used in the literature to control for unobserved heterogeneity associated with the insurance decision (see below).

Selection into insurance based on both observables and unobservables can be simultaneously dealt with by combining the above methods. For instance, regression-based models that deal with unobservables (such as Heckman sample selection model) also account for selection on observables by including observed covariates in the OOP expenditure regression model (Jowett et al 2003) [24]. Another common example of jointly addressing selection on observable and unobservables is by combining propensity score matching (for selection on observables) and difference-in-difference method (for selection on unobservables). For example, Axelson et al (2009) [39] use propensity score matching to control for observable differences between insured and uninsured, and difference-in-difference approach to control for time-invariant unobserved factors that may be correlated with outcomes. This approach has been commonly used in the insurance literature [19] [40] [41] [42]. Wagstaff et al (2010) [43] extend this approach by combining propensity score matching with triple differencing which involves subtracting two previous difference-in-differences in outcome measures from two later difference-in-differences measures using available data for three periods.

However, the methods discussed above only account for differences in unobservables in one of the two decisions (generally the insurance-seeking decision) but not both.

To put this mathematically, the insurance-seeking decision can be represented by a probit model:

$$\Pr[Insurance = 1] = \Phi(\beta_v V_i + \varepsilon_i^{INS}) \qquad (4)$$

Here $V$ represents the predictors of insurance-seeking decision. Selection bias arises when there is correlation the error terms in equation 4 and equation 1, or between the error terms in equation 4 and equation 3.

Finally, the unobserved factors associated with the care seeking decision may be associated with the purchase of insurance. This paper proposes a regression-based method to account simultaneously for both care-seeking and insurance-seeking selection biases.

## 3. DATA AND METHODS

For the purpose of illustrating our methods, we use household survey data from Vietnam collected in the year 1999. These data were originally analysed by Jowett et al (2003) [24]. However, those authors only accounted for insurance-purchase/participation selection and did not take account of care-seeking selection bias. Our study illustrates how to jointly account for both insurance-purchase/participation and care-seeking selection biases. We provide a short paragraph of background on the Vietnamese health insurance programme below, to help readers understand the policy context of this illustrative empirical analysis.

Vietnam introduced health sector reforms in the 1980s, which resulted in the introduction of user fees for services that were previously available free of charge. Between 1993 and 1998, public sector user fees rose by over 1,000% in real terms. During the same time period, fees for private health professionals rose by almost 600%. In 1993, Vietnam introduced its health insurance programme, which included compulsory health insurance for civil servants, and voluntary health insurance (the subject of this analysis) for formal and informal sector employees, the unemployed and children. In 1998, about 12% of the Vietnamese population were covered by the insurance programme, with a little over half covered by the VHI programme [44].

### 3.1. Data

The data and sampling methods are described in detail in Jowett et al (2003) [24] and briefly summarised here. Data were collected through one-to-one questionnaire-based interviews conducted in three provinces with reasonably high membership rates, i.e. Hai Phong and Ninh Binh in the north-east and Dong Thap in the south-west. Within each province, one urban and two rural districts were randomly sampled, followed by random sampling of three communes within each district, followed by random sampling of insured and uninsured individuals with each commune. A total of 1,650 adults and 1,101 children were interviewed, of which 19% were residents of Ninh Binh, 40% of Hai Phong and 41% of Dong Thap. The survey collected data on baseline demographics, health insurance status, health care utilisation, out of pocket payments and self-reported health status for the three months period prior to the interview. The socioeconomic status of the respondent was recorded using annual household consumption expenditure in the last 12 months, which was adjusted for the household size using the following equivalence scale [45]:

$$Equivalence\_factor = (No.of\ adults + \emptyset * No.of\ children)^{\theta} \qquad (5)$$

Following Wagstaff et al (1999) [46], the two unknown parameters $\emptyset$ and $\theta$ were set equal to 0.5. Since the proportion of insured individuals in the population was small, the survey design oversampled the insured members by increasing their sampling frequency. For the purpose of analysis, sampling weights were used to account for the sampling structure.

From a total sample of 2,751 interviewees, 1,192 individuals reported being ill in the past three months, of whom 985 sought health care and incurred out of pocket expenditure. Respondents were asked to recall direct health care expenditures (i.e. user fees for consultations, diagnostic tests and medicines), indirect expenditures (food and hospital stay, travel and other expenditures) and any unofficial payments (i.e. gifts to health care providers). OOP expenditure was then defined as the sum of these expenditures in the analysis. Data on insurance premiums had substantial non-responses, possibly because many individuals purchased their policy several months before the survey. Therefore, following Jowett et al (2003) [24], the premium amount was not included in estimations of healthcare expenditures for the insured. The resulting underestimation of expenditures for the insured is unlikely to be substantial, given the low level of premiums relative to average health expenditures amongst insured patients[24]. However, this does not matter for our methodological purposes of illustrating the differences between standard methods and our proposed new method of allowing for care-seeking and insurance-seeking selection when estimating out of pocket expenditures. The lack of complete data on premia paid does however mean that the "true" impact of VHI on reducing total health care expenditures will be slightly over-estimated by both the standard and the proposed models.

### 3.2. Econometric models

We used four approaches to model the impact of VHI on out of pocket health care expenditure. The approaches differed in terms of whether or not the model accounted for care-seeking and insurance-seeking selection biases. All models take as their dependent variable the log of the observed individual-level out of pocket expenditure on health care. Individuals who did not seek health care, despite reporting illness, had zero observed expenditure. Since the log of zero is undefined, a positive constant (+1) was added to the expenditure for all individuals. Household consumption expenditure was also log-transformed because of the skewed distribution. All models used heteroskedasticity-robust standard errors. The econometric models are described below.

#### 3.2.1. Model 1: Ordinary Least Squares (OLS) model for expenditure on care

Model 1 is a naïve OLS regression represented by equation 1; it uses (log) observed health care expenditure for both care-seeking and non-care-seeking individuals.

$$Expenditure_i = \alpha + \beta_1(Insurance)_i + \beta_x X_i + \varepsilon_i^Y \qquad (1)$$

Since the expenditure on care equation is semi-logarithmic, the coefficient on insurance variable was transformed using equation (6) [47] to estimate the percentage impact of insurance on expenditure on care.

$$Transformed\_coefficient = \exp\left(\beta - \frac{1}{2}Var(\beta)\right) - 1 \qquad (6)$$

Here $\beta$ is the untransformed regression coefficient on the insurance variable and *var*($\beta$) is the variance of the untransformed coefficient. The coefficient on the insurance variable represents the impact of insurance membership on out-of-pocket expenditure. The OLS model ignores selection on unobservables resulting in care-seeking and insurance-seeking self-selection biases.

#### 3.2.2. Model 2: Heckman's sample selection model to account for care-seeking selection only

Model (2) accounts for care-seeking selection bias by using Heckman's sample selection approach that jointly estimates the care-seeking decision and the expenditure equation (OLS) conditional on care-seeking. This model involves two equations: (a) a care-seeking sample selection equation that models the selection decision [equation 3]; and (b) a expenditure equation using log of health care expenditure for individuals who sought care [equation 7], i.e. the dependent variable is non-zero expenditure conditional on seeking care.

$$\Pr[Care - seeking] = \Phi(\beta_z Z_i + \varepsilon_i^{cs}) \qquad (3)$$

$$Expenditure_i | \, (care - eseeking = 1) = \alpha + \beta_1 (Insurance)_i + \beta_x X_i + \varepsilon_i^h \qquad (7)$$

Heckman's model jointly estimates equations (3) and (7) using maximum likelihood estimation, which allows for correlation between the unobserved determinants of the care-seeking decision and the healthcare expenditure equation (correlation coefficient $\rho$). The model was identified using functional form assumptions about joint normality in correlation of the error terms However, this model only accounts for care-seeking selection but ignores the insurance selection bias.

#### 3.2.3. Model 3: Treatment effects model to account for insurance selection only

To account for the endogeneity of the insurance decision, Heckman's treatment effects model is commonly used [25] [24] [18] [31]. The treatment effects model also contains two equations: (a) a selection equation which models the insurance-seeking decision [equation 4]; and (b) an unconditional expenditure equation [equation 1] which uses log of health care expenditure for both insured and uninsured individuals for both care-seeking and non-care seeking individuals.

$$\Pr[Insurance = 1] = \Phi(\beta_v V_i + \varepsilon_i^{INS}) \qquad (4)$$

$$Expenditure_i = \alpha + \beta_1 (Insurance)_i + \beta_x X_i + \varepsilon_i^Y \qquad (1)$$

The treatment effects model jointly estimates the insurance-seeking probit model and the healthcare expenditure model using maximum likelihood estimation. This allows for correlation between the unobserved determinants of the insurance decision and the healthcare expenditure equation. As noted by Wagstaff et al. (2010) [43], the model makes the assumption that there are no further unobserved benefits from insurance for individuals who choose insurance (i.e. the estimates of the effect of insurance for the insured can be generalised to the uninsured if they were to receive insurance). However, the treatment effects model ignores the care-seeking selection bias. It further differs from Heckman's sample selection model (model 2) in two aspects: (a) the endogenous choice variable (i.e. insurance variable) directly enters the outcome (expenditure) regression; and (b) expenditure is observed for both choice groups (i.e. insured and uninsured).

The treatment effects model relies on uniquely identifying the insurance selection process [equation 4] from the outcome equation [equation 1] using predictors, also known as instrumental variables (or simply instruments), that uniquely predict the selection decision, i.e. they are correlated with the insurance decision but uncorrelated with OOP expenditures except through their effect on insurance. In the current study, the following binary variables were used as instrumental variables to identify the insurance-seeking decision: 'respondent knows that VHI subsidises drugs expenditures'; 'respondent knows where to buy VHI card'; 'respondent is a member of other mass/community organisation'; 'respondent has medium to high level of worry about personal future health'. Also, since insurance membership was sought more than three months before the survey, the following variables are used to identify the healthcare expenditure (outcome) equation: 'hospital inpatient stay in the last three months' and 'the number of illnesses in the last three months'.

### 3.2.4. Model 4: Two part selection model to account for both care-seeking and insurance-seeking biases

The previous two models separately corrected for either care-seeking or insurance-seeking selection bias, but not both. Since the healthcare expenditure model can potentially suffer from both kinds of biases, a dual-selection model (model 4) is proposed here to jointly account for the two selection decisions.

The model has two selection-correction parts:

- The first part is an insurance decision model – this is simply the insurance probit model which is presented in the equation below (same as equation 4 before):

$$\Pr[Insurance = 1] = \Phi(\beta_v V_i + \varepsilon_i^{INS}) \qquad (4)$$

This insurance decision model is used to estimate the so-called Inverse Mills' Ratio (IMR) ($\lambda i$) for each person in the sample. IMR represents the unobserved propensity to purchase/participate in insurance, given that insurance was available. If, based on known characteristics, the predicted probability of insurance-seeking is high and the individual is observed to have purchased/participated insurance, then the influence of unobserved variables (and hence the IMR) would be small, and vice versa [48]. It can be represented mathematically as:

$$\lambda_i = \begin{cases} \phi_i\,(\beta_v V) \big/ \Phi_i\,(\beta_v V) & \text{for insured} \\ \phi_i\,(\beta_v V) \big/ [1 - \Phi_i\,(\beta_v V)] & \text{for } uninsured \end{cases} \quad (8)$$

IMR is then used in the second part of the model (see below) to account for unobserved propensity of purchasing/participating in insurance. As before, equation (4) is estimated with exclusion restrictions, (instrumental) variables that uniquely predict insurance membership but not care-seeking or OOP expenditures (i.e. the second part of this model).

- The second part is the Heckman sample selection model for the care-seeking decision – this is the same as model 2 (presented earlier) but this time augmented by a correction term known as Inverse Mills Ratio which is obtained from the first component of the model above. This IMR term is used as a covariate in both the care-seeking and OOP expenditure parts of Heckman selection model (model 2).

The reason for using IMR from the selection (insurance) equation in the outcome equation is that selection bias is essentially an omitted variable bias, which occurs due to unobserved factors that predict insurance decision and are also correlated with care-seeking decision and OOP expenditure. Inclusion of the IMR term as a covariate in the care-seeking and OOP expenditure equations helps to capture the correlation between unobserved predictors of insurance and outcome equations and therefore helps to correct for the selection bias. If the IMR in the expenditure equation is significant and negative, it implies a negative correlation between unobservables in the insurance participation and OOP expenditure. In other words, unobserved factors that decrease insurance participation will also tend to reduce OOP expenditure. Hence, the final healthcare expenditure equation accounts for the insurance-seeking selection through the inclusion of the IMR from the first part (4a) of the model (i.e.

the insurance probit) and also accounts for care-seeking selection by jointly estimating the expenditure and care-seeking equations in the second part to allow for error correlation.

The final care-seeking and OOP expenditure equations are estimated jointly using Heckman's sample selection correction maximum likelihood model can be represented as:

$$\Pr[Care - seeking] = \Phi(\beta_z Z_i + \beta_s IMR + \varepsilon_i^{cs}) \qquad (9)$$

$$Expenditure_i | \,(care - seeking = 1) \\ = \alpha + \beta_1 (Insurance)_i + \beta_x X_i + \beta_c IMR + \varepsilon_i^t \qquad (10)$$

Here equation (9) is the care seeking selection equation, while equation (10) is the expenditure equation conditional on care having being observed/sought. Both equations include IMR as covariate to account for unobserved predictors of the insurance decision. These equations are estimated jointly using Heckman maximum likelihood estimation procedure.

## 4. RESULTS

This section starts by describing the raw data, comparing unadjusted mean differences in healthcare expenditure between insured and uninsured groups by socioeconomic groups, before turning to the econometric results.

### 4.1 Descriptive statistics

The descriptive statistics for the variables of interest are presented in Appendix A1. Most respondents were residents of rural areas and 41% of them were farmers by profession. The insured made up 20.25% of the sick sample, and were likely to be more educated and in hired employment. Figure 1 summarises health care expenditures as proportions of total household consumption expenditure. As one would expect, although richer quintile groups incurred higher expenditures of care in absolute monetary terms, the proportion of income sacrificed was substantially lower than in the poorest quintile groups. The figure shows that the proportionate shares were consistently lower for the insured group.

*(Figure 1 about here)*

**4.2 Regression results**

The regression models used in this study estimate the impact of insurance membership on healthcare expenditure. The analysis was carried out using Stata version 12.1. The unit of analysis was an individual for whom the questionnaire was completed.

Table 1 presents the main results from the expenditure models.

*(Table 1 about here)*

The OLS analysis was carried out on all individuals who reported illness over the past three months. The observed expenditure for those who did not seek care was zero. The OLS model takes both zero and non-zero values as expenditures, and does not explicitly model the care-seeking decision. The OLS model passed the Ramsey RESET test with test score $F(3, 1{,}164) = 0.32$ and $p > F = 0.81$, and had an R-squared value of 0.25. OLS results show a statistically significant negative effect of insurance membership on the log of health care expenditure [Table 1]. After the transformation in equation (6), the OLS model estimates that insurance membership reduced OOP expenditures by 51.3% (see figure 2). Regression results also show that the socioeconomic status of an individual is positively related to their observed healthcare expenditure, suggesting positive income elasticity which makes intuitive sense. Expenditure on health care was also observed to have a strong positive relationship with inpatient admissions and long-term health care status. Patients who self-assessed their health as fairly bad, or those who were suffering from long-term illness, incurred substantially higher expenditure than those in good health.

The OLS model does not correct for potential care-seeking and insurance-seeking selection bias. Following Waters (1999) [49], we tested for the presence of care-seeking and insurance-seeking selection biases by separately introducing the predicted probabilities from the care-seeking and insurance-seeking probit models into the OLS model. Statistically significant coefficients (care-seeking: p = 0.02; insurance-seeking: p = 0.00) indicated the presence of selection biases.

Heckman's sample selection model (model 2) is employed to allow for care-seeking selection by joint estimation of healthcare expenditure and care-seeking equations. The coefficient on insurance in the Heckman model was much higher at -0.949 compared to -0.676 in the OLS model [Table 1], suggesting that the correlation between the residuals of the care-seeking probit and healthcare expenditure models should not be ignored. The *rho* parameter for independence of the care-seeking and expenditure equations in the sample selection model was weakly significant (p = 0.06). After the transformation based on equation [6], the impact of insurance was estimated to be 63.1% (see figure 2). The coefficient on log of consumption expenditure also showed a small increase after correction for care-seeking bias. We also evaluated the coefficients in the care-seeking equation in the model that suggest that socioeconomic and insurance status does not significantly influence the decision to seek care [Table 2], although insurance significantly reduces the healthcare expenditure when treatment is sought.

Model 3 is the treatment effects model that accounts for the potential endogeneity of the insurance decision. This model has been commonly employed in the literature and aims to correct for insurance selection bias by independently identifying insurance-seeking decision whilst jointly estimating the healthcare expenditure model. However, the model ignores any potential care-seeking selection bias. The insurance-seeking equation was identified using instrumental variables that identify the insurance-seeking process. Following Waters (1999) [49], the appropriateness of the identifying variables was tested by introducing the identifying variables on the right hand side of a reduced form probit equation for the insurance-seeking decision. Statistically significant coefficients on identifying variables indicated that the variables were appropriate candidates. Subsequently, the identifying variables were included on the right hand side of the healthcare expenditure model to establish that they did not significantly predict the expenditure model.

The coefficient on the insurance variable in model 3 was -1.086, compared to -0.676 in the OLS model, suggesting that the OLS model had underestimated the impact of insurance membership on healthcare expenditure. Following equation [6], the impact of insurance on healthcare expenditure was estimated to be 69.0% (see figure 2). The *rho* parameter for independence of the insurance-seeking and expenditure equations in the sample selection model was statistically significant (p = 0.01) indicating significant correlation between the residuals of the insurance-seeking probit and healthcare expenditure models. We also evaluated the coefficients in the insurance-seeking equation in the model that suggest that years of schooling and rural residence were positively associated with insurance seeking decision, while female gender, wage employment and chronic illness were negatively associated with the insurance-seeking decision. The coefficients on identifying variables suggest that the insurance decision was indeed positively associated with medium to high level of worry about future health, membership of mass organisation and knowledge about the benefits of VHI and where to get the membership card.

Models 2 and 3 account for either care-seeking or insurance-seeking selection decisions but not both. Model 4 aims simultaneously to account for the two types of selection decisions by introducing the IMR term from the insurance probit (the first part of model 4) into the Heckman sample selection equations in the second part of the model (i.e. the healthcare expenditure and care-seeking equations). IMR and its squared and cubic forms have different levels of statistical significance in the selection part of the model. Large values of the t-ratio associated with the IMR term suggest the presence of sample selection bias [50].

Results from model 4 show that the effect of IMR in the healthcare expenditure model was positive and concave, suggesting that the unobservable factors associated with the insurance decision are associated with higher healthcare expenditures but at a diminishing rate. In the care-seeking model, IMR was found to have a negative effect on the probability of seeking care. The Wald statistic for independence of the care-seeking and healthcare expenditure equations rejected the null-hypothesis of no correlation [p>z = 0.01]. Most importantly, the coefficient on insurance membership in model 4 was -1.238 compared to -0.676 in the OLS model, suggesting that the naïve model significantly underestimated the impact of insurance by ignoring selection biases. When the coefficient was transformed using equation [6], the magnitude of the impact was 72.3% compared to 51.3% estimated in the OLS model (see figure 2). This shows that not accounting for the selection biases underestimated the impact of voluntary insurance by 21 percentage points.

*(Figure 2 about here)*

## 5. DISCUSSION

This paper develops an approach to account simultaneously for insurance-seeking and care-seeking selection biases in modelling the impact of VHI on health care expenditures. We illustrate these methods using survey data on the impact of a Vietnamese voluntary health insurance programme on individual out-of-pocket health care expenditure. The naïve OLS model suffers from important selection biases due to care-seeking and insurance-seeking decisions. This is because correlation between the expenditure on care and unobserved determinants of the care-seeking and insurance-seeking decisions is likely to produce biased estimates. Although previous studies have allowed for insurance-seeking selection bias, these studies have not allowed for simultaneous care-seeking selection. The contribution of this paper is to propose and illustrate a method for simultaneously allowing for both forms of selection bias. In our illustrative example, we use four different econometric models to compare the results of naive OLS against models allowing for each form of bias, both separately and jointly.

Results from the naïve OLS model suggest that insurance membership reduces out of pocket expenditure by 51.3%. When both insurance-seeking and care-seeking decisions were taken into account, however, the impact of insurance on reducing health care expenditures increased to 72.3%. Moreover, results also confirmed the presence of correlation between health care expenditure and unobserved determinants of the selection decisions.

The relative magnitude of the impact of the two selection decisions on insurance coefficients in the expenditure model will depend on the level of selection bias in a particular study. The care-seeking bias is important in the case of low-income countries with predominantly out-of-pocket healthcare systems where the decision to seek care is often correlated with the expected healthcare expenditure. The impact of correcting for care-seeking bias is likely to be higher when insurance status is a strong predictor of the care-seeking decision, i.e. the insured have a higher probability of seeking care when ill. This was not found to be the case in the illustrated example of Vietnam, but studies in other contexts have found that the insured are more likely to seek care when ill and to seek care from higher-level providers [18] which would result in higher expenditures in the insured group.

We compared our results with Jowett et al (2003) [24] who used the same data but only corrected for insurance selection but ignored the care-seeking selection bias. The final coefficient of the impact of insurance on OOP expenditures was higher in Jowett et al, i.e. -1.6 compared to our final estimate of -1.24. This is because they estimated the impact of insurance for individuals who sought care, and therefore benefitted more from insurance membership in terms of reduction in OOP expenditures. Therefore, the estimate from Jowett et al [24] is not generalisable to the wider population who need health care, and is also not directly comparable to our estimates.

Our illustrative analysis found that socioeconomic status had a positive and statistically significant relationship with out of pocket health care expenditures. However, richer quintile groups were found to pay less as a percentage of their total consumption expenditure, consistent with the findings in other studies of Vietnam[51, 52]. This mirrors broader concerns about inequity in health care financing in low-income countries that have been extensively discussed in the literature [53] [30] [54].

The study also finds that insurance membership did not have a statistically significant impact on the probability of care-seeking, suggesting that other factors may play an important role in the care-seeking decision. One such factor may be geographical access to health services, since province of residence is associated with the care-seeking decision. 94.05% of the sick residents of Dong Thap sought care, compared to 66% and 86% of residents from Hai Phong and Ninh Binh provinces, respectively.

We also modelled the probability of health insurance uptake, which was found to be positively associated with the socioeconomic status of an individual. Richer individuals were more likely to purchase insurance, and in turn to benefit from expenditure reduction. This is likely to have equity implications, especially if the insurance fund is subsidised through government funding.

Our study uses data on a relatively small health insurance programme targeting just three provinces of Vietnam to illustrate our method of accounting for double selection bias. However, the issue of double selection bias is also likely to occur in larger programme evaluations with broader populations. Indeed, one might anticipate that as programmes target and evaluate broader populations the insurance-seeking element of bias may reduce – because there is less scope for selection – whereas the care-seeking element of bias may increase.

This is because broader programmes are likely to include older, sicker and more disadvantaged populations who are likely to face greater care-seeking barriers. Moreover, selection biases also depend on the type of coverage and benefits of health insurance programme as well as the study context. For instance, while compulsory health insurance programmes are generally not affected by insurance-seeking adverse selection, they may still suffer from care-seeking selection issue. In case of Vietnam, Sepehri et al (2011) evaluated both compulsory health insurance (CHI) and voluntary health insurance (VHI) programmes and found that the impact of CHI on reducing OOP healthcare expenditure was higher than VHI. This may be partly because VHI is more likely to be influenced by adverse selection. Similarly, coverage (such as type of services and health facilities covered) and level of insurance co-payment may also the impact of insurance and the influence insurance-seeking and care-seeking selection biases.

In case of Vietnam, a number of studies have used a national dataset from different waves of the Vietnam Household Living Standard Survey (VHLSS) to evaluate the impact of different types of health insurance programmes. Appendix table A3 summarises the methods and results of studies evaluating the impact of health insurance in Vietnam. These studies evaluate one or more of the following insurance programmes in Vietnam: (1) voluntary health insurance (VHI); (2) compulsory health insurance (CHI); (3) Vietnam Health Care Fund for the Poor (VHCFP); and (4) free healthcare for children under 6 years. These studies come to different conclusions which are summarised here. Sepehri et al. (2006) [25] evaluated both VHI and CHI together using VHLSS for 1992-3 and 1997-8 and corrected for care-seeking bias using Tobit model (fixed and random effects) but not accounting for insurance endogeneity. They found that insurance reduce OOP expenditure by 17% to 20%. Jowett et al (2003) used the same dataset as our study (i.e. survey of three provinces in year 1999), and corrected for insurance endogeneity but not care-seeking bias (and only used positive OOP expenditure observations). They found that VHI significantly reduced OOP expenditure, although their coefficients are much larger than ours results because they only used observations with positive OOP expenditures (therefore, their model results cannot be generalised to the wider population). Finally, Nguyen (2012) [6] evaluated the impact of VHI using VHLSS 2004 and 2006 using PSM and double differencing (i.e. difference-in-difference) to account for insurance selection and found that the effect of VHI on OOP expenditures is not statistically significant; however, they found that insurance increases the annual outpatient and inpatient visits by 45% and 70% respectively which partly explains no statistically significant reduction in OOP expenditure despite insurance reducing the price of care.

Wagstaff (2007) [55] evaluated VHCFP programme in Vietnam using VHLSS 2004 wave using propensity score matching (PSM) for insurance selection and found that it did not reduce the average out-of-pocket expenditure because it increased the probability and number of inpatient and outpatient visits. The same programme was evaluated by Axelson *et al* (2009) using PSM followed by double differencing for insurance endogeneity, and by Wagstaff (2010) using PSM followed by triple differencing to account for both observed and unobserved heterogeneity (see Appendix for details). Axelson *et al* (2009) found that VHCFP reduced only inpatient OOP but not overall expenditure, while Wagstaff (2010) found that VHCFP reduced both inpatient OOP and total OOP expenditures. Finally, Sepehri *et al* (2011) evaluated CHI, VHI and VHCFP using VHLSS waves 2004 and 2006 using fixed and random effects models and found that CHI and VHI reduced OOP expenditure at district hospitals by 40% and 32% respectively but did not reduce expenditure for those using commune health centres.

The above studies account for observables, and in most cases also unobservable, of the insurance-seeking decision (through PSM or regression with/without difference-in-difference methods). However, none of these studies simultaneously accounted for care-seeking and insurance-seeking biases which may partly explain some of these differences in findings [56].

The focus of our study was on selection on unobservables, while also accounting for observable differences using regression model. As noted earlier, selection on observables can be dealt with using different approaches, with regression and matching methods being the most popular in the literature. We found in our data that respondent characteristics were similar for most observed characteristics, and more importantly, the predicted propensity for insurance had complete overlap (i.e. common support). Based on this, the choice of method for dealing with observable difference is unlikely to be significant in this study. Moreover, neither regression nor matching account for selection on unobservables. Finally, our proposed approach for selection on unobservables can be easily applied to matching methods using weighted propensity score method.

There are also other econometric approaches available in the literature that account for selection on unobservables [57] [58]. At least one of them, i.e. the instrumental variable approach, has been shown to be equivalent to Heckman's sample selection model when selection decision is binary (which is the case in this study) [59]. Further research can explore if using other selection models produce similar results.

The modelling approach used in this study is relevant to non-randomised settings evaluating the effect on insurance on OOP expenditures. Randomised studies, such as the RAND health insurance experiment [60], which allocated individuals to different health insurance plans, are likely to have balanced groups in terms of their unobserved propensity to seek care (by virtue of randomisation). As a result, the average treatment effect can be estimated without the need to account for selection biases. However, most health insurance studies are not randomised, and therefore need to consider the issue of care seeking selection bias. Allowing for sample selection bias implies estimates can be generalised to individuals who did not seek care [61], which addresses the important question of 'What would have been the effects of health insurance had these individuals sought care?'.

The study has some limitations. Firstly, identification of the care-seeking equation relied on non-linearity of the inverse Mill's ratio. Whilst this is the common practice when instrumental variables are not available [50], the care-seeking decision may be better identified with unique instrumental variables. For the insurance-seeking selection, we used instrumental variables, though of course identification is only as good as the instrumental variables used. Secondly, Heckman's selection model assumes bivariate normality of error terms of the selection and outcome equations. The consequences of violation of this assumption should be explored in future work. Thirdly, whilst our proposed approach controls for the first hurdle, i.e. the care-seeking decision, it did not completely control for the quantity and quality of healthcare received. In a case study of China, Wagstaff and Lindelow (2008) [18] found that insurance encouraged individuals to seek care and to seek care from higher-level providers, which will have an effect of the estimation of true impact of insurance on OOP expenditure. Finally, insurance premiums were unknown for most respondents and, hence, were not included in the analysis. This means that all models will over-estimate the impact of voluntary insurance; however, the overestimation is unlikely to be substantial, given the low level of premiums relative to average health expenditures amongst the insured.

In conclusion, when access to health care is determined primarily by ability to pay, out-of-pocket payments are one of the most significant barriers to health care access, resulting in an inequitable distribution of health and health service utilisation [44] [62]. Hence, evaluation of the impact of VHI and other schemes on reducing out of pocket expenditures is important, in order to find both expenditure-effective and equitable ways of extending financial protection mechanisms to improve access to health care. This study has developed a method for allowing simultaneously for both care-seeking and insurance-seeking selection biases, and has highlighted the significance of employing unbiased econometric models for estimating the impact of health insurance on the healthcare expenditure. In the context of low-income countries, where substantial numbers of individuals may be deterred from seeking care due to geographical and financial barriers to access, it is important to allow for care-seeking selection bias as well as insurance-seeking selection bias. Finally, our method can be generalised to evaluation of other types of health insurance programmes (such as social insurance) if they include an element of choice for the enrolment and care-seeking decisions that can be influenced by expected future healthcare expenditures.

**Figure 1: OOP health care expenditure as percentage of total consumption expenditure**

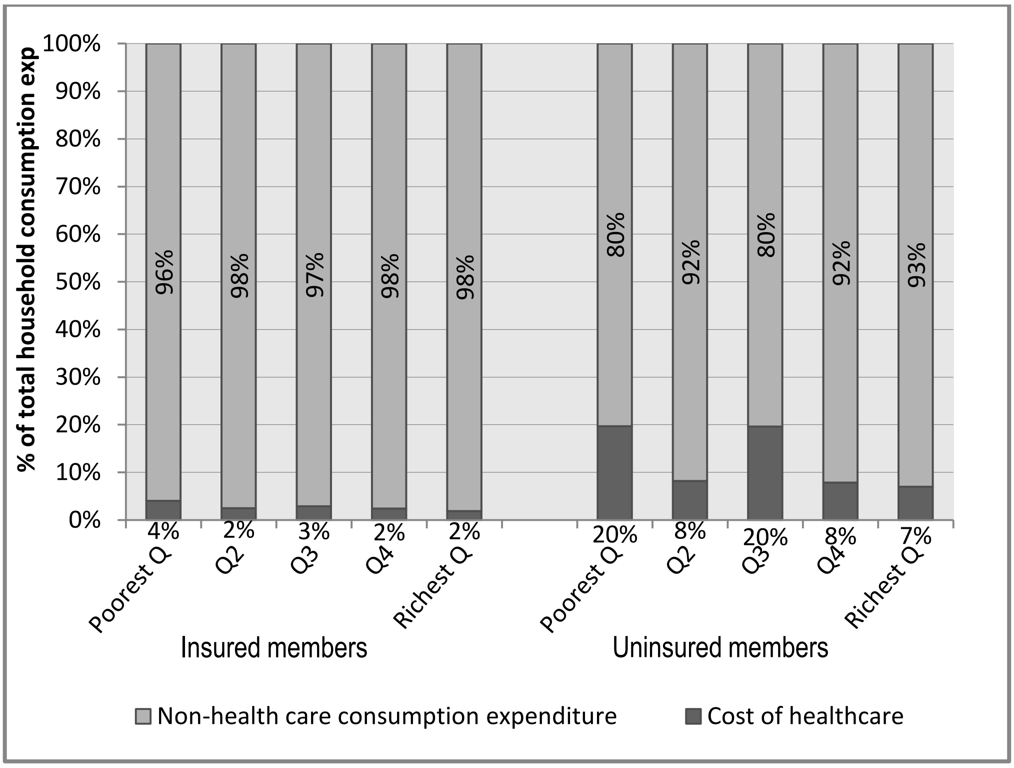
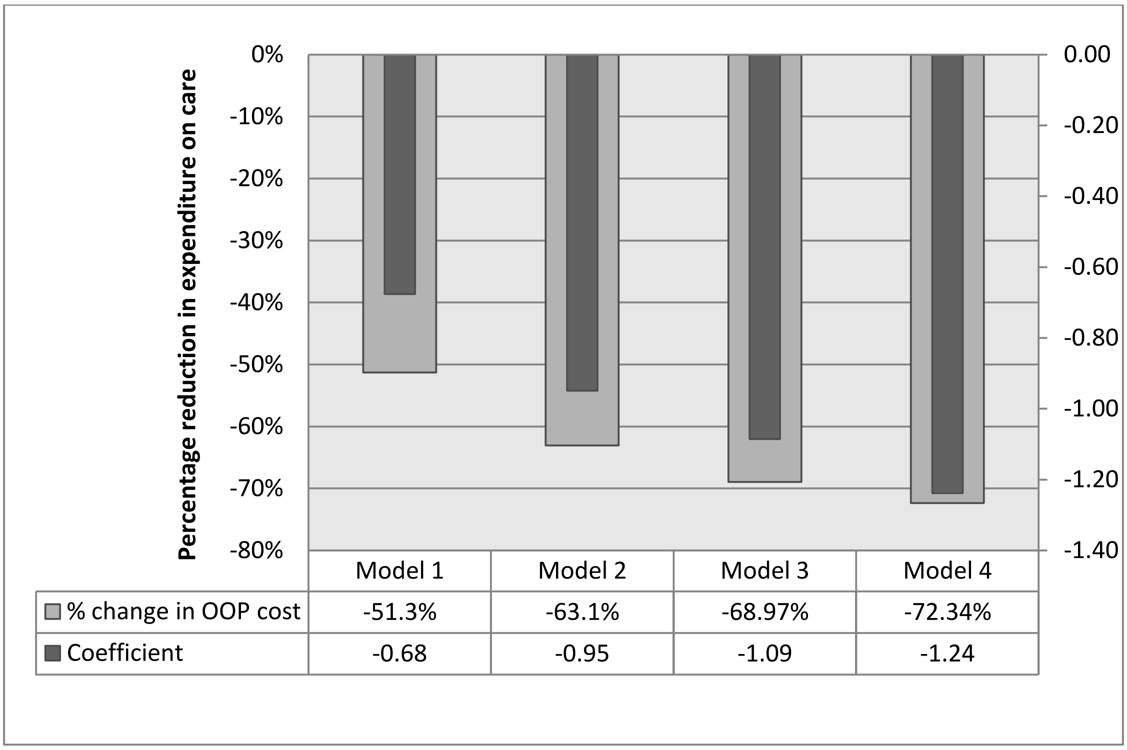


**Figure 2: Impact of insurance membership on out-of-pocket healthcare expenditure**




| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| % change in OOP cost | -51.3% | -63.1% | -68.97% | -72.34% |
| Coefficient | -0.68 | -0.95 | -1.09 | -1.24 |

**Table 1: Results of econometric analysis of healthcare expenditure**

| **Dependent variable: Log of individual level healthcare expenditure** | **Model 1: OLS** | **Model 2: sample selection model allowing for care-seeking selection** | **Model 3 - Treatment effects model allowing for insurance-selection** | **Model 4: Sample selection model allowing for both care-seeking and insurance-selection** |
|---|---|---|---|---|
| Member of VHI | -0.676** | -0.949*** | -1.086*** | -1.238*** |
| programme | (0.03) | (0.00) | (0.01) | (0.00) |
| Log of equivalent annual | 0.419** | 0.459*** | 0.437** | 0.488*** |
| household expenditure | (0.03) | (0.00) | (0.01) | (0.00) |
| Age | 0.008 | 0.006 | 0.006 | 0.002 |
| | (0.65) | (0.71) | (0.75) | (0.90) |
| Age-squared | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.76) | (0.66) | (0.87) | (0.82) |
| Female | 0.041 | -0.184 | 0.033 | -0.193 |
| | (0.91) | (0.51) | (0.93) | (0.51) |
| Interaction between age | 0.004 | 0.010 | 0.005 | 0.010 |
| and sex | (0.59) | (0.14) | (0.56) | (0.13) |
| No. of illnesses in last 3 | -0.028 | 0.010 | -0.029 | 0.010 |
| months | (0.65) | (0.84) | (0.63) | (0.83) |
| Inpatient admission in last | 2.332*** | 2.488*** | 2.320*** | 2.467*** |
| 3 months | (0.00) | (0.00) | (0.00) | (0.00) |
| Health status: fairly good | 0.061 | -0.201 | 0.031 | -0.243 |
| | (0.82) | (0.46) | (0.91) | (0.39) |
| Health status: fairly bad | 0.800** | 0.721*** | 0.796*** | 0.700** |
| | (0.02) | (0.01) | (0.01) | (0.01) |
| Health status: long-term | 0.909** | 0.698* | 0.906** | 0.675* |
| Illness | (0.03) | (0.06) | (0.02) | (0.07) |
| Chronic illness | 0.099 | 0.103 | 0.077 | 0.076 |
| | (0.76) | (0.72) | (0.80) | (0.78) |
| Rural residence | 0.304 | 0.317 | 0.316* | 0.332* |
| | (0.12) | (0.12) | (0.09) | (0.10) |
| Province: Hai Phong | -0.524 | -0.008 | -0.549 | -0.004 |
| | (0.23) | (0.99) | (0.20) | (0.99) |
| Province: Ninh Binh | 0.011 | 0.144 | -0.017 | 0.115 |
| | (0.96) | (0.62) | (0.93) | (0.68) |
| Occupation: service | 0.270 | 0.385** | 0.250 | 0.350* |

| | | | | |
|---|---|---|---|---|
| | (0.28) | (0.03) | (0.31) | (0.05) |
| Occupation: farmer | 0.021 | -0.040 | -0.004 | -0.077 |
| | (0.90) | (0.85) | (0.98) | (0.72) |
| Occupation: wage employment | -0.166 | -0.252 | -0.185 | -0.284 |
| | (0.31) | (0.18) | (0.24) | (0.14) |
| Years of schooling | -0.022 | -0.010 | -0.014 | -0.002 |
| | (0.53) | (0.75) | (0.67) | (0.96) |
| Interaction between schooling and gender | 0.001 | -0.008 | 0.002 | -0.008 |
| | (0.96) | (0.71) | (0.95) | (0.74) |
| Interaction between schooling and age | 0.001 | 0.001 | 0.000 | 0.001 |
| | (0.50) | (0.30) | (0.55) | (0.34) |
| Inverse Mills' Ratio | - | - | - | 0.471* |
| | - | - | - | (0.08) |
| Inverse Mills' Ratio – squared | - | - | - | -0.236*** |
| | - | - | - | (0.00) |
| Inverse Mills' Ratio - cube-root | - | - | - | 0.018 |
| | - | - | - | (0.48) |
| Constant | -0.635 | -0.791 | -0.701 | -0.892 |
| | (0.66) | (0.51) | (0.62) | (0.45) |
| Rho | - | 1.269* | 0.224** | 1.197* |
| | - | (0.06) | (0.01) | (0.05) |
| Sigma | - | 0.406*** | 0.479*** | 0.398*** |
| | - | (0.00) | (0.00) | (0.00) |
| Observations | 1189 | 1189 | 1189 | 1189 |
| R-squared | 0.26 | - | - | - |

Robust p values in parentheses *** p<0.01, ** p<0.05, * p<0.1

**Table 2: Intermediate probit models of care-seeking and insurance-seeking decisions**

| Covariates: | Care-seeking model (part of model 2) | Care-seeking model with correction for insurance-selection (part of model 4) | Insurance-seeking model (part of model 3) |
|---|---|---|---|
| Member of VHI programme | -0.254 | 0.317 | - |
| | (0.33) | (0.50) | - |
| Log of equivalent annual | 0.185 | 0.190 | 0.355* |
| household expenditure | (0.31) | (0.33) | (0.10) |
| Age | -0.015 | -0.013 | -0.265*** |
| | (0.64) | (0.68) | (0.00) |
| Age-squared | 0.000 | 0.000 | 0.002*** |
| | (0.60) | (0.64) | (0.00) |
| Female | 0.259 | 0.302 | -1.333*** |
| | (0.70) | (0.67) | (0.00) |
| Interaction between age and sex | -0.001 | -0.001 | 0.048** |
| | (0.94) | (0.92) | (0.03) |
| No. of illnesses in last 3 months | -0.092 | -0.088* | - |
| | (0.10) | (0.09) | - |
| Health status: fairly good | 0.416 | 0.464* | -0.525** |
| | (0.15) | (0.08) | (0.02) |
| Health status: fairly bad | 0.334 | 0.351 | 0.679* |
| | (0.29) | (0.23) | (0.07) |
| Health status: long-term | 0.682 | 0.716 | 0.590 |
| Illness | (0.29) | (0.23) | (0.44) |
| Chronic illness | -0.003 | -0.009 | -1.720*** |
| | (0.99) | (0.98) | (0.00) |
| Rural residence | 0.078 | 0.074 | 0.988* |
| | (0.75) | (0.75) | (0.08) |
| Province: Hai Phong | -1.196*** | -1.171*** | -2.117*** |
| | (0.00) | (0.00) | (0.00) |
| Province: Ninh Binh | -0.551* | -0.531** | -2.080*** |
| | (0.05) | (0.04) | (0.00) |
| Occupation: service | 0.039 | 0.035 | -0.838* |
| | (0.92) | (0.93) | (0.07) |
| Occupation: farmer | 0.224 | 0.241 | -0.345 |
| | (0.45) | (0.42) | (0.58) |

| | | | |
|---|---|---|---|
| Occupation: wage employment | 1.463 | 1.539* | -1.213** |
| | (0.11) | (0.05) | (0.05) |
| Years of schooling | -0.033 | -0.037 | 0.166*** |
| | (0.59) | (0.58) | (0.00) |
| Interaction between schooling | 0.012 | 0.010 | 0.029 |
| and gender | (0.83) | (0.85) | (0.74) |
| Interaction between schooling | 0.000 | 0.000 | 0.007*** |
| and age | (0.78) | (0.77) | (0.01) |
| Respondent has medium to high level of worry about future | - | - | 1.888*** |
| health | - | - | (0.00) |
| Member of a mass organisation | - | - | 0.909*** |
| | - | - | (0.00) |
| Do you know where to go get hi | - | - | 2.432*** |
| card? | - | - | (0.00) |
| Do you think or know of any benefit of VHI when getting | - | - | 0.597*** |
| medicines? | - | - | (0.01) |
| Inverse Mills' Ratio | - | -0.221 | - |
| | - | (0.57) | - |
| Inverse Mills' Ratio – squared | - | -0.244** | - |
| | - | (0.02) | - |
| Inverse Mills' Ratio - cube-root | - | 0.047* | - |
| | - | (0.09) | - |
| Constant | 0.270 | 0.142 | -4.885*** |
| | (0.86) | (0.93) | (0.00) |
| Observations | 1189 | 1189 | 1189 |

Robust p values in parentheses *** p<0.01, ** p<0.05, * p<0.1

## Appendices

### Table A1: Descriptive statistics for the variables of interest

| | Respondents reporting sickness in the last 3 months (N=1,192) | Sick respondents who sought health care (N=982) | Insured who were also sick (N=242) | Uninsured who were also sick (N=950) |
|---|---|---|---|---|
| **Variable Name** | **Mean** | **Mean** | **Mean** | **Mean** |
| Member of Voluntary Health Insurance (percentage of respondents) | 20.25 | 17.09 | - | - |
| Age (years) | 35.86 | 35.95 | 34.80 | 32.42 |
| Female (percentage of respondents) | 55.75 | 56.70 | 38.59 | 56.38 |
| Rural resident (percentage of respondents) | 81.81 | 82.22 | 72.20 | 71.65 |
| Resident of Hai Phong (percentage of respondents) | 8.32 | 6.43 | 31.95 | 7.17 |
| Resident of Ninh Binh (percentage of respondents) | 28.33 | 27.67 | 4.98 | 48.89 |
| Resident of Dong Thap (percentage of respondents) | 63.35 | 65.90 | 63.07 | 43.94 |
| Occupation – service/business (percentage of respondents) | 11.55 | 11.28 | 8.71 | 10.33 |
| Occupation – farmer (percentage of respondents) | 41.28 | 41.12 | 25.31 | 29.82 |
| Occupation - hired (percentage of respondents) | 6.80 | 7.38 | 8.30 | 5.48 |
| Occupation – student (percentage of respondents) | 22.32 | 21.18 | 22.82 | 35.83 |
| Occupation – retired (percentage of respondents) | 7.68 | 7.36 | 2.90 | 6.74 |
| Occupation - other (percentage of respondents) | 10.37 | 11.68 | 3.32 | 12.96 |
| Number of years of schooling | 5.32 | 5.18 | 8.19 | 6.03 |
| Health status - good (percentage of respondents) | 20.27 | 18.64 | 37.76 | 21.29 |

| | | | | |
|---|---|---|---|---|
| Health status - fairly good (percentage of respondents) | 51.54 | 52.66 | 37.34 | 52.90 |
| Health status - fairly bad (percentage of respondents) | 16.21 | 16.33 | 14.11 | 11.70 |
| Health status - long-term illness (percentage of respondents) | 11.99 | 12.37 | 10.79 | 14.12 |
| Chronic illness (percentage of respondents) | 14.78 | 15.16 | 12.45 | 13.28 |
| Number of illnesses in the last 3 months | 2.01 | 2.02 | 2.08 | 1.88 |
| Inpatient care (yes) (percentage of respondents) | 10.19 | 9.82 | 13.25 | 9.20 |

Table A2: Average health care expenditures per person in the last three months (by consumption quintiles)

| | **Poorest quintile (‘000 VND) (N = 239)** | **Quintile 2 (‘000 VND) (N = 238)** | **Quintile 3 (‘000 VND) (N = 238)** | **Quintile 4 (‘000 VND) (N = 240)** | **Richest quintile (‘000 VND) (N = 236)** | **Total (‘000 VND) (N = 1,192)** |
|---|---|---|---|---|---|---|
| Insured | 29.85 | 29.86 | 45.87 | 52.95 | 98.99 | 66.69 |
| Uninsured | 176.40 | 101.29 | 356.28 | 159.15 | 283.30 | 212.76 |
| Average | 174.758 | 98.418 | 322.697 | 170.794 | 268.020 | 206.091 |

**Table A3:** Summary of published studies evaluating the impact of health insurance in Vietnam

| Study | Data | Type of analysis | Results |
|---|---|---|---|
| Jowett *et al* (2003) | Single cross-sectional survey conducted in year 1999 using purposive sampling to evaluate the voluntary component of Vietnam's voluntary health insurance (VHI) programme – before the introduction of Vietnam Health Care Fund for the Poor (VHCFP). Survey conducted in 3 provinces (Ninh Binh, Hai Phong and Dong Thap). This data is the same as used in our paper. | Heckman's two-step regression was used to correct for insurance endogeneity. First step was a probit regression for probability of insurance. Inverse Mills Ratio (IMR) was obtained from this model and included in the OLS regression for out-of-pocket (OOP) expenditure. The expenditure equation included only non-zero values for health expenditure; hence, care-seeking selection was ignored. | Overall, health insurance was found to reduce average out-of-pocket expenditures. The dependent variable was the log of out-of-pocket expenditure. The coefficient on insurance was -2.080 (p=0.001) after correcting for insurance endogeneity which was interpreted incorrectly as 200% reduction in expenditure. |
| Sepehri *et al* (2006) | National data from 1992-3 and 1997-8 waves of the Vietnam Living Standards Survey (VLSS) to evaluate Vietnam's health insurance programme; however, unlike Jowett *et al* (2003), both compulsory (predominant) and voluntary health insurance was included and jointly evaluated because VLSS did not provide distinction between the two types. | Two approaches were used with panel individual effect: (1) Tobit model which treats zero expenditure as censored (i.e. censored value for selecting into care, not insurance); and (2) truncated regression which uses only positive expenditure. Fixed and random effects models were used.<br><br>Insurance endogeneity bias was not taken into account, partly because both compulsory and voluntary insurance was included. | Random and fixed effects models produce different results. Final set of results show that health insurance reduces out-of-pocket health expenditure (between 17 and 20%). |
| Wagstaff (2007) | National data from VHLSS 2004. The study evaluated VHCFP which was introduced in 2003. | Propensity score matching was used to account for insurance endogeneity, followed by regression weighted by propensity score weights. | Total out-of-pocket health expenditure is reduced by VHCFP in the simple PSM but not with the regression. The study concluded that VHCFP did not reduce average out-of-pocket expenditure because it increased the probability and number of inpatient and outpatient visits. A secondary finding was that VHCFP reduced the risk of catastrophic spending by 3-4%. |

| Study | Data | Type of analysis | Results |
|---|---|---|---|
| Axelson *et al* (2009) | VHLSS data from 2002 (pre-VHCFP) and 2004 (post-VHCFP) | First analysis used PSM for selection into insurance followed by single differencing (i.e. difference in OOP expenditure between insured and uninsured at one time point) in a cross-section analysis of VHLSS 2004. Second analysis used PSM followed by double differencing (or difference-in-difference, i.e. first calculating the mean difference in outcome before and after the intervention for the insured and uninsured groups separately, followed by calculating the difference between the mean differences of the two groups). This is done using panel dataset for VHLSS 2002 and 2004; the double differencing is to take account of time-invariant unobserved factors. | The result from the double differencing differs from single-differencing. Single differencing found statistically significant reduction in OOP expenditure at household level by 19% (although reduction in per capita expenditure of 14% was not significant). Results of difference-in-difference also found reduction in health care expenditure but they were only significant for inpatient care expenditure (absolute reduction of 134.6 Vietnamese Dong). |
| Wagstaff (2010) | VHLSS data from the panel element of the 2002, 2004 and 2006 waves. | Triple-differencing which involves difference-in-difference over three periods, i.e. besides the double difference-in-difference between insured and uninsured (as above), a further difference is taken to 'net out' the difference between the same groups in the change in mean OOP expenditure over an earlier period. Instead of assuming parallel trends in the unobservables for the insured and uninsured groups, it assumes that the change in unobservables for each group in the two periods (2002-2004) and (2004-2006) is the same. This method can be used with regression or matching to control for observables.<br>The proposed method estimates programme impact on those covered by it but not | Single-difference with matching found no significant impact of VHCFP on out-of-pocket expenditure. Double and triple-differencing found significant negative impact on total OOP expenditure (-181 and -327 VND respectively) and OOP expenditure on inpatient care (-131 and -248 VND respectively). |

| Study | Data | Type of analysis | Results |
|---|---|---|---|
| | | those currently not covered. | |
| Sepehri *et al* (2011) | VHLSS data from the panel element of the 2004 and 2006 waves. The focus is on compulsory health insurance (CHI), VHI and insurance for the poor. | Fixed and random effects models were used. Fixed effects analysis was intended to control for time-invariant unobserved individual effects. Endogeneity bias due to adverse selection into insurance was not taken into account. | Random effects analysis showed that CHI and VHI reduce OOP expenditure by about 24% while health insurance for the poor reduces it by 15%. However, in the fixed effects analysis, the coefficients for CHI and VHI were not significant. Further analysis showed that CHI and VHI reduce OOP expenditures by 40 and 32%, respectively for those using district hospitals but not significant for commune centres. |
| Nguyen (2012) | VHLSS data from the panel element of the 2004 and 2006 waves. The focus is on voluntary health insurance. | PSM followed by double differencing (i.e. difference-in-difference). | The effect of voluntary health insurance on out-of-pocket expenditure on health care services is not statistically significant; however, insurance increases the annual outpatient and inpatient visits by 45% and 70% respectively which partly explains no statistically significant reduction in OOP expenditure despite insurance reducing the price of care. |
| Nguyen and Wang (2013) | VHLSS data from the panel element of the 2004 and 2006 waves. The focus was on evaluating a government policy to provide free healthcare for children younger than 6 years. The policy came into effect in the beginning of 2005. | Difference-in-difference approach using VHLSS wave 2004 (pre-policy) and 2006 (post-policy) in a regression model controlling for potential confounders. | Free health insurance reduced OOP health expenditure by US$5.09 in the age group 4-7. It also reduced the probability of having catastrophic OOP expenditure by 1.7 percentage point. |

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*Ethics approval/Statement EA not required

**Ethics statement:**

This study used already published secondary data from a household survey conducted in Vietnam. We can confirm that Ethics Approval was not required for this work.

We also confirm that this manuscript is the original work of the authors. It has not been previously published and is not under review in any other journal. All authors have contributed to the paper, have approved its submission, and take responsibility for its contents. The paper and its figures are currently within SSM's length requirements. We of course would be happy to re-organise materials based on the editors' suggestions.