

## **Be rich or don't be sick: Estimating Vietnamese patients' risk of falling into destitution**

**Quan Hoang Vuong**

This paper represents the first research attempt to estimate the probabilities for Vietnamese patients to fall into destitution facing financial burdens occurring during their curative stay in hospital. The study models the risk against such factors as level of insurance coverage, location of patient, costliness of treatment, among others. The results show that very high probabilities of destitution, approximately 70%, apply to a large group of patients, who are non-resident, poor and ineligible for significant insurance coverage.

There is also a probability of 58% that low-income patients who are seriously ill and face higher health care costs would quit their treatment. These facts will put Vietnamese government's ambitious plan of increasing both universal coverage (UC) to 100% of expenditure and rate of UC beneficiaries to 100% at a serious test. The study also raises issues of asymmetric information and alternative financing options for the poor, who are most exposed to risk of destitution, following market-based health care reforms.

Keywords: Health insurance; Government policy on health care; Risk of destitution.

JEL Classifications: I13; I18; I19.

**CEB Working Paper N° 14/031  
December 2014**

**Be rich or don't be sick:  
Estimating Vietnamese patients' risk of falling into destitution**

Quan Hoang Vuong, Ph.D.  
Centre Emile Bernheim, Université Libre de Bruxelles  
50 Ave F.D. Roosevelt, Bruxelles 1050, Belgium  
Email: qvuong@ulb.ac.be

First draft:  
December 18, 2014 at 01:00AM

**Abstract:**

This paper represents the first research attempt to estimate the probabilities for Vietnamese patients to fall into destitution facing financial burdens occurring during their curative stay in hospital. The study models the risk against such factors as level of insurance coverage, location of patient, costliness of treatment, among others. The results show that very high probabilities of destitution, approximately 70%, apply to a large group of patients, who are non-resident, poor and ineligible for significant insurance coverage. There is also a probability of 58% that low-income patients who are seriously ill and face higher health care costs would quit their treatment. These facts will put Vietnamese government's ambitious plan of increasing both universal coverage (UC) to 100% of expenditure and rate of UC beneficiaries to 100% at a serious test. The study also raises issues of asymmetric information and alternative financing options for the poor, who are most exposed to risk of destitution, following market-based health care reforms.

**Keyword:** Health insurance; Government policy on health care; Risk of destitution

**JEL code:** I13; I18; I19

**Acknowledgements:** I would like to thank friends and colleagues who have provided assistance and support for this research: Nghiem Phu Kien Cuong (Viet Duc Hospital, Hanoi), Le Nga and Tran Tri Dung (DHVP Research), Nguyen Pham Muoi (Wall Street Journal), Dau Thuy Ha (OCD Consultants). My work also benefits from discussions with Nancy K. Napier and Kirk Smith (Boise State University, ID, USA), Donaldine E. Samson (Stamford International University, Bangkok). Apparently, I am indebted to hundreds of patients and their family members for willingness to answer our deep, and often time-consuming, interviews, without whose information this study would hardly be possible.

## **Be rich or don't be sick: Estimating Vietnamese patients' risk of falling into destitution**

Quan Hoang Vuong

### **1. Introduction**

Today's Vietnam has a large population of 92 million, with a low per capita GDP of approx. \$2,000 in 2014. Financial hardship is quite common among the populace, both in urban and rural areas. The poverty issue is even much more serious with families having a seriously sick member.

On November 13, 2014, an article on *Dan Tri*—one of the most popular online media in Vietnam—reported a story about the poor mother-patient Nguyen Thi Lan in Thach Lap Commune, Giong Rieng District, Kien Giang (a southern province of Vietnam). She suffered from a serious brain tumor that led to uncontrollability of behavior. She unintentionally dropped her one-year-old daughter five times. Her husband told *Dan Tri*'s reporter that the family was too poor and could not afford travel and health care cost, so they had to keep her home and try to cure the disease with “traditional medicine” without progress. That article made numerous readers empathetic to her family's plight. Many sent money to help. On December 15, 2014, 47 million Vietnamese Dong (VND), approx. \$2,200, was collected from various readers and sent to her family. With social attention, Mrs. Lan would be able to travel to a provincial hospital and start being treated (*Dan Tri Online*, 2014). The number of stories like this is uncountable on newspapers in Vietnam. Apart from showing public care about the hardship of their country fellows, such articles also give rise to the issue of efficiency and use of health insurance, treatment costs and the general degree of financial destitution that many poor patients, and their families, are faced with.

Now that the amended Law on Health Insurance has been enacted, effective from January 2015. The new law seeks to increase universal coverage (UC) to 100%, and aims to provide 100% of Vietnamese with insurance benefits, compulsory or voluntary. The state expects that the new law will help reduce exposure of society, especially the poor, to the risk of destitution—which has for decades now been a harsh reality—caused by extreme medical care costs that uninsured patients have little choice but to pay.

Apparently, the problem is hardly new. More than 13 years ago, Whitehead, Dahlgren & Evans (2001) discussed on *The Lancet* about the problem of patients risking falling into ‘the medical poverty trap’, giving a ballpark figure: “In rural North Vietnam, 60% of poor households were in debt, with a third citing payment for health care as the main reason” (p. 834). The authors in closing the article called for researchers and policy-makers' attention to poverty-alleviation strategies bearing the medical costs to vulnerable sections of society in mind (p. 836). Their excellent research has attracted a huge attention from both public and the scholarly community, thus more articles have since been published addressing this big issue in developing countries.

Later, Russell (2004) also pointed to the fact that in poor Asian countries, cost burdens of illness were high and regressive on patients and households. Russell (2004) stressed the need for further microeconomic research on the household costs of illness and implications for poverty, having anticipated a serious economic burden of illness for households in developing. He wrote: “International research efforts also need to develop a common illness cost and impact methodology to allow more meaningful comparisons of the economic burden of illness across settings and diseases” (Russell 2004: p. 152). We can't agree more with the author on this.

The understanding of impact of illness on risk of becoming financially distressed is more challenging due to scarcity of socioeconomic data. Quality of information for policy making is thus limited and seriously

affected. Also development of financing mechanisms for helping cover treatment costs has seen not much progress and still an issue for debate. Medical costs usually serve to be a ‘shock’ to household’s well-being. Coping with it, either normal illness or catastrophic event, has to deal with issue of increasing levels of debt and without understanding of probability of falling into poverty trap, it will be hard to devise effective strategies (Russell 2004: p. 153).

This article represents a new attempt to examine factors, including insurance coverage, household socioeconomic status, costliness of medical services, length of hospital stay, among others, that may cause the risk of destitution to increase using a 330-patient survey data set obtained from direct interviews with patients, and households, who were hospitalized during 2014.

The paper starts with a literature review on health studies on Vietnam’s health care system, with a clear emphasis on assessment of impacts on poverty and in relation to health insurance. Then it moves on with a section of research method of baseline category logit, which is employed to model the conditional probabilities of going destitute upon some specific events. The key section reports estimated results, together with computed probabilities, which should shed light on some key research questions stated. Toward the end, the paper provides a discussion on key insights and implications for stakeholders, including patients, health service providers and the state.

## **2. Literature review**

Various researchers have made serious attempts to study about issues relating to health care systems, medical costs, the ‘poverty trap’, health reform policy-making... and shed light on numerous aspects of low-income countries’ health care sector. This section of review focuses solely on issues related to the Vietnamese health care sector, with a clear emphasis on factors possibly increasing risk of poverty, especially for the poor, that have empirically been verified.

Bloom (1997) see the need of ‘radical health sector reforms’ for low-income countries, and states that China and Vietnam could exemplify a model of financing health services, especially in the rural areas. But both countries face the issue of rising health costs and inequalities among groups of different income levels. In 1990s, a high proportion of rural people in Vietnam were able to consult with health worker in the community, and to him: “This suggests that access to basic health services is reasonably good.”

But things have changed as the market modus operandi comes into play. The author provides some useful statistics. The richest quartile of rural Chinese spend 3.2 times as much on medical care as the poorest quartile, citing a World Bank survey in 1996. The figure for Vietnam was 4.6 times in 1994. Health care charges have become a burden for the poor, with rural Chinese spending up to 5 times the average daily per capita income on a average prescription, and Vietnamese spending 8% of the annual nonfood consumption for each visit to a commune health care station (Bloom 1997: p. 16). The risk of falling into financial hardship jumps when there is a seriously ill family member, as average hospital admission could cost 60% of the annual net income of poor households in China, and average commune health unit admission costs 45% of a poor family’s annual nonfood consumption in Vietnam. The event can cause increasing debts and asset sales, and becomes an important cause of poverty. The poor has too few financing options. The economic reforms have led to the situation in which the relationships between health workers, government and patients have altered, and health service providers now favor the rich, to whom they can supply expensive drugs and sophisticated technologies (Bloom 1997: pp. 17-18).

As to financing alternatives for the majority of patients, Sepehri, Chernomas & Akram-Lodhi (2003) verify that Vietnam’s health care system has undergone some major structural reforms, which significantly affect the delivery and financing of health services. Emerging issues are access, efficiency and equity in health services sector, amid the trend of dwindling state funding and a shift from state

finance to out-of-pocket fees at patients' expenses (p. 156). The rich tend to receive more health care, with longer hospital stays, intensive resources use. The poor receive proportionally less care, with a rising trend of over-provision of services and expensive drugs, leading medical care cost to become increasingly higher among various living costs. According to, this is a direct consequence of declining state funding and lack of alternative financing for poor patients, as well an efficient regulatory mechanism (Sepehri et al 2003: p. 157).

Specifically, Lönnroth, Tran, Thuong, Quy & Diwan (2001) point to the fact that 'evening clinic' treatment of tuberculosis by private physicians may cost 200,000 to 1,000,000 Vietnamese Dong/month (\$13 to \$67). As to many households, that amount was a 'heavy' financial burden. Apart from fees and drugs, patients and households were also worried about time-consuming process that usually triggered discontinued income during treatment period and the cost of travel. Loss of income and the cost of travel together could exceed fees and costs of drugs (Lönnroth et al 2001: p. 940). The authors noticed that already from this period, health service providers have aimed at profits, leading to unnecessary tests (for fees) and prescribing unnecessary, usually expensive, drugs (for profits and commissions from pharmaceuticals suppliers) (p. 943).

In a broader and highly influential research, Whitehead, Dahlgren & Evans (2001) unveil that poor households reporting illness in a rural area in northern Vietnam, spent an average 22% of their household budget on health-care costs, whereas rich households spent 8% (p. 834). That is why 'home remedies' have still been a preferred choice, representing 'the cheapest healthcare option' although the average cost rose progressively due to prices of drugs and consultations (Segall, Tipping, Lucas, Dung, Tam, Vinh, & Huong, 2002: p. 500). Segall et al. (2002) also notice that non-poor households spent over average much more than the poor, their average cost per admission was 150% monthly income. The lowest cost by the poor represented 200% of monthly income, therefore debt remained pervasive among the poor as a major financing option for healthcare services. In rural area of Vietnam, 3.3-10% of annual income was devoted to health care— while the average 2-7% was typical in a variety of developing countries—leading many Vietnamese households to also sell rice reserves and livestock, apart from borrowings, to finance health costs (Segall et al 2002: pp. 501-2).

In the same vein, Ha, Berman & Larsen (2002) confirm the burden on households in rural area and report that severely ill people tended to use public care (p. 61), although public services showed a tendency of consuming more resources than private ones (p. 67). The authors estimate that the amount of subsidy was quite small, in fact negligible, accounting for around 4% of total expenditure (p. 68). Also, new issues emerge to exacerbate the problem of health care financial burden, as Ensor (2004) adds that "there is growing evidence to suggest that unofficial health care fees are likely to distort health care priorities and change the impact of health system reform" in developing countries (Ensor 2004: p. 245).

As to factors giving rise to risk of poverty, Sepehri et al. (2005) postulate a possible link between income and the length of hospital stay as in transition economies post-hospital follow-up is virtually non-existent and travel is costly. According to the authors, a longer stay may increase assurance, reduce post-treatment complications and readmission, or simply speaking: better-quality care (p. 97). They suggest further investigations to examine effects of unofficial and official payments on the intensity and quality of health care (p. 98) and the differences between groups of patients.

The 'implied' risk of inflating financial burden has become clearer with unreported out-of-pocket (OOP) payments by patients. Van Doorslaer et al. (2006) survey 11 countries and unveil that in Vietnam (as well as Bangladesh, China, India, Nepal), more than 60% of health care costs are paid out-of-pocket, and OOP health payments exacerbate poverty (p. 1357). 2-7% of the population in the 11 low-income countries may fall below the extreme poverty threshold (\$1/day) due to health care payments. They also suggest

careful and well-controlled evaluations to learn more about specific reforms in health financing that could help reduce impoverishment due to payments for health care (pp. 1362-4).

Again, Van Doorslaer et al. (2007) look into the issue of OOP and confirms the OOP share remains highest in Bangladesh, India and Vietnam, with 10.6–12.6% of non-food expenditures spent on health care (p. 1169). Chaudhuri & Roy (2008) reports that OOP payment in 2002 is positively related to per capita consumption, and increases for higher consumption quintile, revealing differences in the redistributive effect. In addition, increases of fees might deter the poor from seeking health services (pp. 42-4).

Also from Van Doorslaer et al. (2007), Bangladesh, China, India and Vietnam continue to have the highest incidence of catastrophic payments (p. 1173). Adding to this observation, in the aspect of ‘financial catastrophe’, Xu, Evans, Carrin, Aguilar-Rivera, Musgrove & Evans (2007) stress the need of moving away from OOP payments, using prepayment systems, installing the so-called ‘financial risk protection strategies’, and increasing funds for alleviating social inequalities in health care (pp. 981-2).

As health sector reform takes place, user fees start proliferating. A major problem with user fees is that, although they help relieve the financial burden on the government, these fees can drive people into poverty and widen the gap between the rich and the poor. The need of measures for protecting the poor is imperative, especially in eliminating unofficial payments and asymmetric information between providers and patients. While only a small proportion of rural residents hold health cards, low insurance coverage also increases the burden on the poor (Dao, Waters & Le 2008: pp. 1076-7).

Another issue is that statistics may be biased due to the finding that the poor are likely to “modify the perception of sickness” to avoid costs due to health care costs and discontinued income (Thuan, Lofgren, Lindholm & Chuc 2008: p. 5). The poor show higher tendency of using self-treatment, while the expenditure for self-treatment is only 13% of total curative expenditure. There is no significant difference between health care fees between the poor and non-poor in public health services, it is likely that public sources may subsidize the rich rather than the poor (Thuan et al 2008: p. 7). In light of this, Ekman, Liem, Duc & Axelson (2008: p. 252) conclude that imperative need for reforming Vietnamese health insurance should focus on: i) sustained resource mobilization; ii) comprehensive functions of the health financing system; iii) a long-term view of health insurance reform. Although roughly 50% of the population benefit from some form of health insurance, only 18% of the poor are entitled to these limited benefits, mainly channeled through the so-called Health Care Funds for the Poor (HCFP); 3/4 of which come from the central government source and 1/4 provincial source (Ekman et al 2008: p. 255). The reality is voluntary health insurance is still not easy and exhibits the asymmetric information issue.

As to health insurance, Liu, Tang, Yu, Phuong, Yan, Thien & Tolhurst (2012) report significant differences in health insurance coverage between Vietnam and China, although the two countries share numerous similar systems and socio-economic properties. Through survey 6 counties in China, they find that coverage rate ranges from 85 to 91% (Shandong province), but the rate is much lower in Vietnam, around 50%, including both voluntary and compulsory schemes. Vietnamese patients with health insurance membership are significantly more likely to utilize inpatient services (Liu et al 2012: p. 5). Vietnamese perceive that health insurance members receive poorer quality of services than non-members, reflecting their complaints that using insurance leads to prescription of only limited types and amounts of medicine with longer waiting time. Thus, it is quite common that insured patients go to private drug sellers for ineligible medicines (Liu et al 2012: p. 6).

The above review tells us about researchers’ agreement on the issues of: a) imperative need for alternative financing for patients in developing countries, in particular Vietnam, and especially for the poor; b) implied risk of falling into destitution for the poor; c) pressing need of better understanding relationships

between socio-economic factors that help explain financial distress faced by the poor; and, d) inadequate protection, at least via health insurance system, for the poor.

### 3. Research questions and method

Although the above-mentioned research studies have significantly contributed to our understanding of the Vietnamese health care systems and issues with patients' hardship, there have been little saying about patients' probabilities of falling into destitution, and related factors that contribute to the level of risk patients have to take when deciding to use health care services. Such insights would likely make the policy making process in Vietnam better-informed, thanks to identifying critical factors and direction of improvements.

#### 3.1. Questions

As we see the above-mentioned room for further improvement of understanding the Vietnamese health sector and patients' risk, answering the following research questions (RS) would complement our knowledge and may help 'prescribe' the next move on the coming health sector reform:

RQ1: Whether status of residency of patients and insurance reimbursement determine the probability of patients to fall into indebtedness? And if the trend is confirmed, does actual level of reimbursement (i.e. coverage) help explain the probability of likely indebtedness, specifically?

RQ2: Among various factors, which would likely be meaningful for explaining the outcome of treatment (or "end result")?

RQ3: Can likelihood of paying little or much "extra thank-you money" –a kind of OOP payment Vietnamese patients usually make by giving "envelop of money" to doctors and hospital staff members– be determined by the severity of illness and/or income of patients?

The third question has usually been regarded as 'sensitive' (everybody-knows-nobody-tells) in transition economies like Vietnam, China, where health care infrastructures are inadequate and underinvested, and there have always been issues with efficiency of public spending on the sector. The issue of "thank-you money" can sometimes become highly political, especially when there appears to be public sentiment towards inefficiency of the system or scandals.

#### 3.2. Research method

The main workhorse for investigating the RQ1-3 is the method of multi-category logit models (also known as, polytomous logistic regression analysis), which models behaviors of multinomial response variable ( $Y$ ) following multinomial (and binomial) predictor variables.

The specific analysis employed in this article is baseline-category logits (BCL). This type of modeling enables us to detect relationships between discrete variables, and in our kind of survey likely polytomous response variables and discrete (multinomial or binomial) explanatory variables, and to compute useful probabilities upon specific events we want to measure influence.

Although log-linear models are also useful in modeling this type of problem, logistic regression is preferred due to: i) fewer and thus more significant variables; ii) direct interpretation of the estimated coefficients in measuring the empirical probabilities of events.

BCL model gives a simultaneous representation of the odds of being in one category relative to being in a designated category, called the baseline category, for all pairs of categories.

In our investigation, a patient (among  $n$  patients) can be regarded as independent and identical, and may have outcome in any of categories for each factor to be investigated. Let  $y_{ij} = 1$  if patient  $i$  has outcome in category  $j$ , and  $y_{ij} = 0$  otherwise. Then,  $\mathbf{y}_{ij} = (y_{i1}, y_{i2}, \dots, y_{ic})$  represents a multinomial trial, with  $\sum_j y_{ij} = 1$ . If we denote  $n_j = \sum_i y_{ij}$  the number of “trials” having outcome in category  $j$ , the count  $(n_1, n_2, \dots, n_c)$  have a multinomial distribution. Let  $\pi_j = P(Y_{ij} = 1)$  denote the probability of outcome in category  $j$  for each patient, then we use the following formula for the multinomial probability mass function:

$$p(n_1, n_2, \dots, n_c) = \left( \frac{n!}{n_1! n_2! \dots n_c!} \right) \pi_1^{n_1} \pi_2^{n_2} \dots \pi_c^{n_c}.$$

This distribution has the following properties:

$$\begin{aligned} E(n_j) &= n\pi_j \\ \text{var}(n_j) &= n\pi_j(1 - \pi_j) \\ \text{cov}(n_j, n_k) &= -n\pi_j\pi_k \end{aligned}$$

where  $\sum_j n_j = n$ .

Now, we let  $\pi_j(\mathbf{x}) = P(Y = j|\mathbf{x})$  represent a fixed setting for predictor variables, with  $\sum_j \pi_j(\mathbf{x}) = 1$ . Count data are grouped into  $J$  categories of  $Y$  as multinomial with corresponding sets of probabilities  $\{\pi_1(\mathbf{x}), \dots, \pi_j(\mathbf{x})\}$ .

The baseline category logit models align each response (dependent) variable with a baseline category, taking the form:

$$\ln \frac{\pi_j(\mathbf{x})}{\pi_1(\mathbf{x})} = \alpha_j + \boldsymbol{\beta}'_j \mathbf{x}, \quad j = 1, \dots, J - 1.$$

BCL analysis simultaneously models the effects of  $\mathbf{x}$  on  $(J - 1)$  logits, which in general vary according to the response paired with the baseline category. The estimating of  $(J - 1)$  equations employing a given empirical data set would provide for parameters for these logits, as:

$$\ln \frac{\pi_a(\mathbf{x})}{\pi_b(\mathbf{x})} = \ln \frac{\pi_a(\mathbf{x})}{\pi_j(\mathbf{x})} - \ln \frac{\pi_b(\mathbf{x})}{\pi_j(\mathbf{x})}.$$

Our empirical data set, which contains count data and mainly uses categorical variables, would enable the computing of Pearson-type likelihood ratio test statistics ( $X^2, G^2$ ) for goodness-of-fit.

The polytomous logistic model is estimated as a multivariate generalized linear model (GLM) which takes the form:

$$\mathbf{g}(\boldsymbol{\mu}_i) = \mathbf{X}_i \boldsymbol{\beta},$$

where,  $\boldsymbol{\mu}_i = E(\mathbf{Y}_i)$ , corresponding to  $\mathbf{y}_i = (y_{i1}, y_{i2}, \dots)'$ ; row  $h$  of the model matrix  $\mathbf{X}_i$  for observation  $i$  contains values of independent variables for  $y_{ih}$ . For a BCL model,  $\mathbf{y}_i = (y_{i1}, y_{i2}, \dots, y_{i,J-1})'$ ; thus  $y_{ij}$  is redundant. Therefore, for BCL:

$$\boldsymbol{\mu}_i = (\pi_1(\mathbf{x}_i), \pi_2(\mathbf{x}_i), \dots, \pi_{J-1}(\mathbf{x}_i))'$$

And,

$$g_j(\boldsymbol{\mu}_i) = \ln\{\mu_{ij}/[1 - (\mu_1 + \dots + \mu_{i,J-1})]\}.$$

A rich account of technical details for practical modeling of polytomous logistic models is provided in Agresti (2002: pp. 267-74). Actual estimations performed in this study—whose results are reported in the next sections—employ analysis in R, following a set of instructions provided by Penn State at <https://onlinecourses.science.psu.edu/stat504/node/171>.

As a main purpose of the estimation is to compute response probabilities from multinomial logits, i.e.  $\{\pi_j(\mathbf{x})\}$ , the following computation will apply:

$$\pi_j(\mathbf{x}) = \frac{\exp(\alpha_j + \boldsymbol{\beta}'_j \mathbf{x})}{1 + \sum_{h=1}^{J-1} \exp(\alpha_h + \boldsymbol{\beta}'_h \mathbf{x})}$$

with  $\sum_j \pi_j(\mathbf{x}) = 1$ ;  $\alpha_j = 0$  and  $\boldsymbol{\beta}_j = 0$ . The computed probabilities can be used to model the risk of a patient to fall into a category of financial distress (indebtedness or destitution) conditional upon some other “events” such as “being in the lower SES group” and/or “being non-resident” as to where the hospital is located, and/or “being insured”, and so on.

#### 4. The data set and estimations

##### 4.1. The survey, data and description

The survey has been conducted by a team including hospital personnel and a Hanoi-based research firm, collecting data from inpatients of several hospitals in the North of Vietnam: Viet Duc Hospital, Bach Mai Hospital, Vietnam-Japan Hospital, Hai Duong Polyclinic Hospital, Thai Binh Polyclinic Hospital, Ministry of Transports Polyclinic, to name a few.

Interviewers approached patients individually and gradually acquired information to fill out the survey form, containing various questions, including questions about “sensitive data” that a more general/social survey could hardly obtain, such as: family status, patient’s income level, patient’s extra expenses to doctors and hospital’s staff, their borrowings to finance treatment.

By approaching some 1000+ patients and their family members, the research team obtained qualified data for 330 patients/households. The process of collecting data has been difficult as various data for each patient need to be obtained while most patients showed their reluctance to answer even a subset of the questions. Enormous patience is thus required. Sometimes a patient had been approached for weeks before that one agreed to answer fully.

The following “variables” will enter the coming analysis process, directly or indirectly:

- “Res”: if a patient is considered “resident” of the region where a hospital is located;
- “Days”: length of stay in hospital
- “Stay” if a patient’s stay in hospital less than 10 days (‘Short’) or equal-or-greater-than (‘Long’)
- “Insured” if a patient is entitled to some insurance coverage under the UC or specific coverage provided by an employer;
- “SES” that has four levels of socioeconomic status for the patient/household: Very high/rich; High; Medium; Low;
- “Illness” representing the severity of sickness of the patient when hospitalized

- “IncRank” showing the income level of a patient;
- “Spent” and “Dcost” represent amount spent during the treatment period and average daily cost paid by the patient, respectively, all in millions of Vietnamese Dong (VND 1 million=\$47.2);
- “Pins; Pinc; Pchar; Ploan”: percentage of payment by sources of insurance coverage, savings, charity funds, borrowings, respectively;
- “Streat, Srel, Senv”: percentage of spending on direct treatment costs, relatives and friends for caring the patient, “thank-you envelop” OOP, respectively;
- “Burden”: levels of financial burden on the patient/household following treatment; and,
- “End”: end outcome of treatment telling if the patient fully recovers, partially recovers, quits in the middle of the process, or quits earlier due to lack of financing options.

Detailed information for all variables and their categorical values are provided in Appendix A1.

An empirical distribution of income and hospital stay among patients constituting the sample in Figure 1. In our data set, these three factors are represented by quantitative variables Age and Days and Income; in millions of Vietnamese Dong (VND) per year. A large portion of our sample is constituted by inpatients who stayed less than 10 days in hospital. Also, a large portion of patients have income lower than VND 50 million (approximately \$2,360) per year, and patients with annual income below \$4,720 account for more than 90% of the sample see Figure (1.a). Likewise, the majority of patients stay less than 10 days in hospital, as indicated in Figure (1.b).

Figure 1 – Frequency distribution of patients’ age and time spent

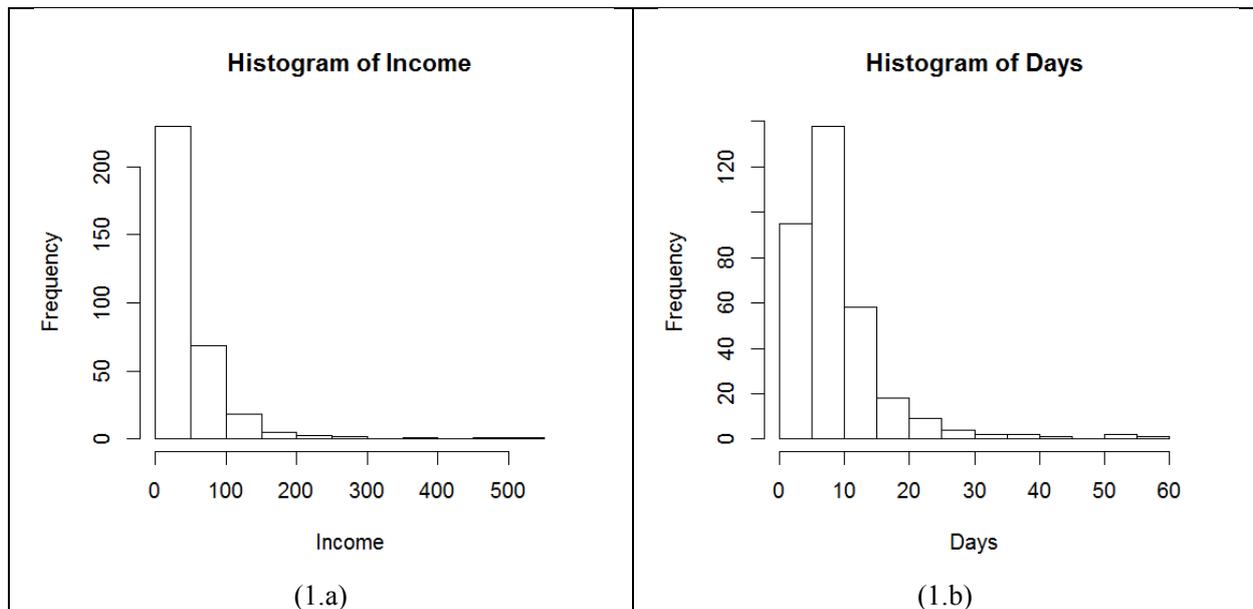
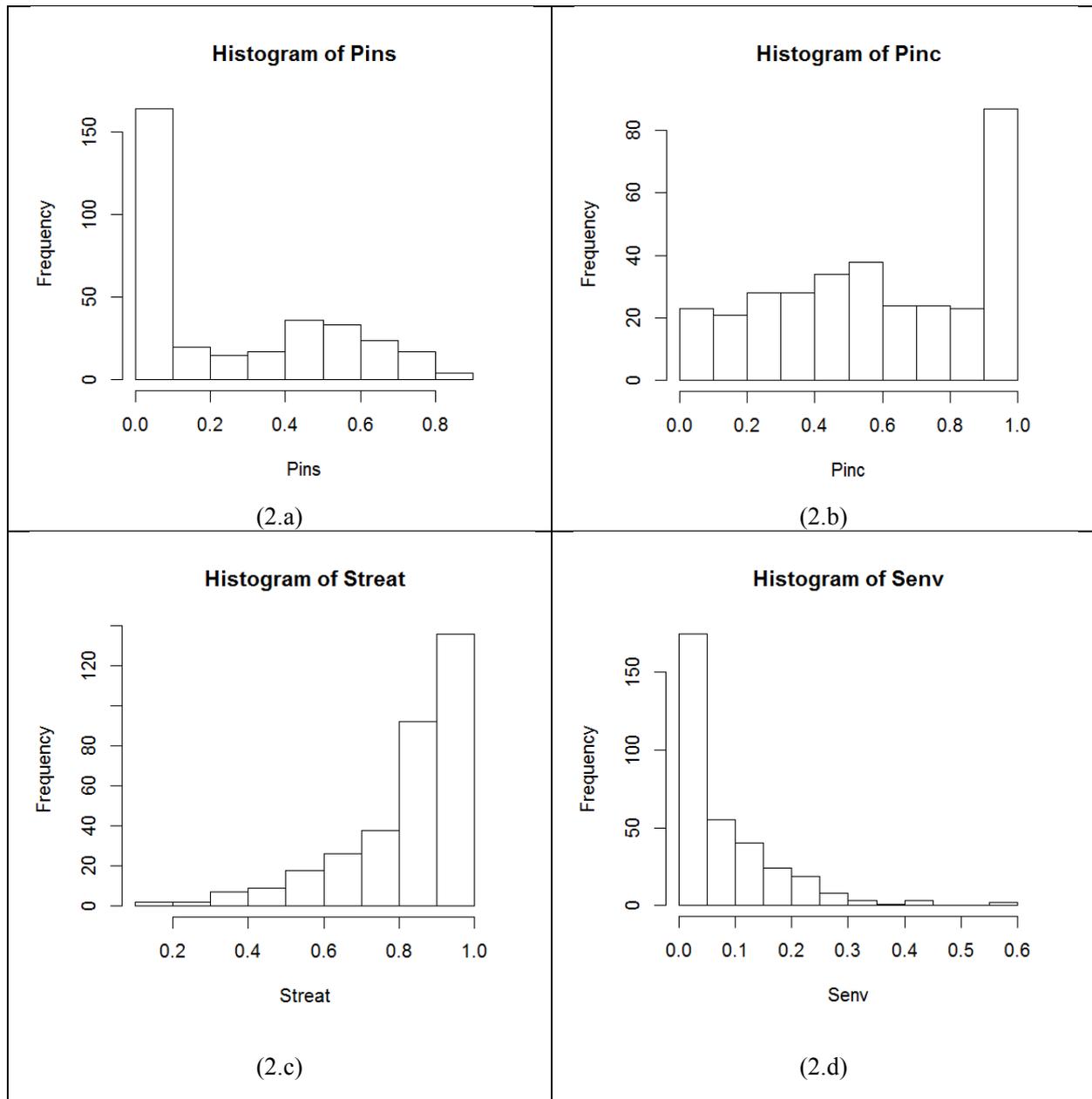


Figure 2 presents sources of finance for paying health care costs by patients, from insurance policy reimbursement (Pins) or from savings from income of patients and their family members (Pinc). These are also quantitative variables measured in percentage. Clearly, a majority of surveyed patients receive less than 50% reimbursement by insurance coverage, and income/savings represents the single most important financing source for paying health care costs for the majority of patients, as indicated by Figure (2.a) and (2.b).

Figure 2 – Sources of finance and cost structure for patients



Likewise, “Streat” in Figure 2 shows frequency for patients to pay their money for main costs of treatment (hospital room, medicines, use of equipment, nurse care,...); “Senv” is the portion of a patient’s total costs for paying extra costs to doctors and hospital’s staff, in the popular form of “envelop” (thank-you money and/or bribe). We can see that the majority of patients’ expenses are for direct treatment costs and hospital service, in the range of 80-100%, while the majority of patients pay less than 15% of total expenses for “thank-you envelop”, thus “Senv” >15% can be considered high portion of an OOP payment.

Figure 3 represents data points, each with 3 numerical values of average daily cost (horizontal axis; in millions of Vietnamese Dong per day; VND 1 million ~ \$47.2), total health care expenses for the treatment (vertical axis; in millions of Vietnamese Dong) and number of days in hospital (taking natural

logarithm to reduce the difference in size effect for better visualization). The differences among patients are apparently quite substantial.

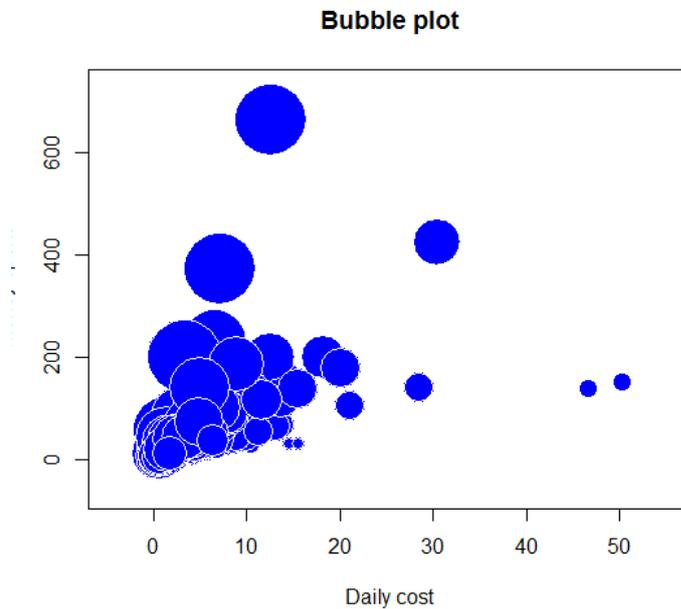


Figure 3 – Daily cost, total expenses and days in hospital

In Figure 4, we can see the most likely length of stays in hospital among patients of this survey, divided into two groups of resident and nonresident. Generally speaking, people coming from other province tend to stay a little longer than those from within the region. However, the difference is not very large and appears to be not quite significant. For each group, dispersion of length of stay can also be large. However, “10 days” appears to be a psychological threshold for patients hospitalized. Later, in our subsequent analysis, 10 days above stay is considered “longer”.

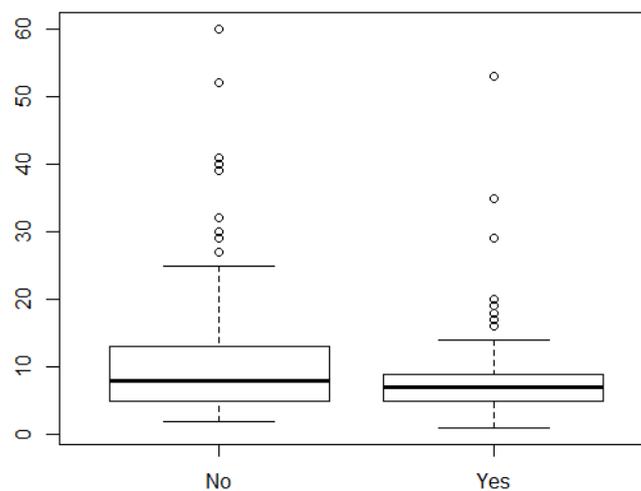
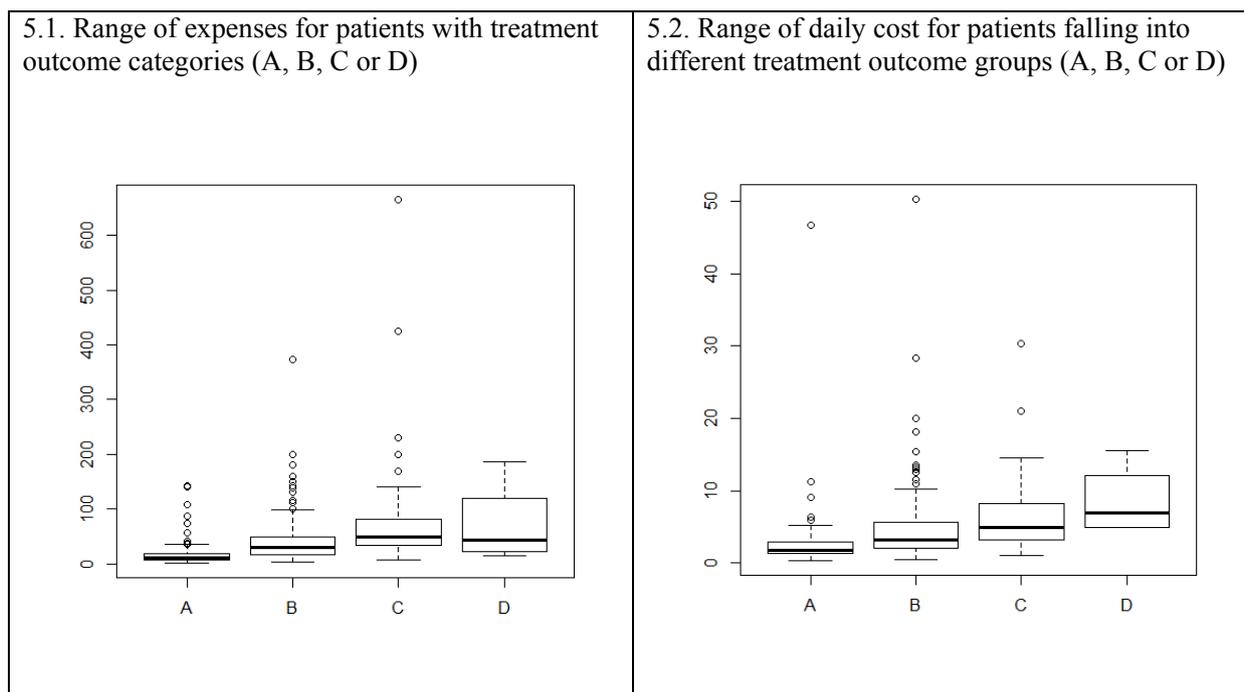


Figure 4 – Distribution of days in hospital among patients, subject to status of residency.

Next, Figure 5 provides two graphs for distributions of total expenses and average daily costs per patient, divided into groups patients with different end results of treatments (A: full recovery; B: partial recovery; C: stopped in middle; D: unsuccessful treatment, even accepting mortality). Both total expenses and average daily costs are with vertical axis, and measured in millions of Vietnamese Dong (VND 1 million = US\$47.2; using official exchange rate as of Oct 15, 2014).

Figure 5 – Status of health in relation to expenditure and average daily cost



Additional graphs are provided in Appendix A2 for visual checks on possible relationship among pairs of variables.

Table 1 provides 5 contingency tables (called “sub-tables”) of categorical response and predictor variables produced for corresponding estimations. Each sub-table is given a name for easier reference in upcoming discussions.

Table 1 – Contingency tables

## BURDEN3					## BURDEN4				
InsL2	Res	A	B	C	AvgCost	InsL2	A	B	C
Hi	No	5	9	41	HiCost	Hi	3	4	22
Hi	Yes	26	11	5	HiCost	Med	1	1	8
Lo	No	4	5	13	HiCost	Neg	4	9	24
Lo	Yes	8	3	1	LowCost	Hi	13	3	4
Med	No	11	1	16	LowCost	Med	8	3	2
Med	Yes	6	6	2	LowCost	Neg	9	10	10
Nil	No	11	24	72	MedCost	Hi	15	13	19
Nil	Yes	14	19	17	MedCost	Med	8	3	8
MedCost	Neg	24	32	69	MedCost	Neg	24	32	69
## BURDEN1					## END2				
##					I112	AvgCost	A	B	C

Resident Insured	A	B	C	Bad Hi	3	33	6
Nonres No	9	23	71	Bad Med	17	59	9
Nonres Yes	22	16	71	Bad Lo	12	8	1
Res No	14	18	14	Emerg Hi	0	8	14
Res Yes	40	21	11	Emerg Med	6	24	17
				Emerg Lo	5	1	1
				Light Hi	3	8	1
				Light Med	34	26	0
				Light Lo	21	12	1
## ENV2							
Ill12 IncRank	Hi	Med	Nil				
Bad HM	7	13	17				
Bad L	8	17	86				
Emerg HM	1	2	9				
Emerg L	9	8	47				
Light Hi	19	13	19				
Light L	16	15	24				

Having checked with statistical standards for categorical data analysis, particularly for polytomous logistic regression, empirical data presented in these sub-tables are satisfactory and ready for the next task of estimations.

#### 4.2. Results: estimated coefficients, functional forms and probabilities

In what follow, 5 estimations with significant coefficients are reported in separate attempts. In each attempt, coefficients are tabulated, followed by equation forms for stylized facts. Estimated probabilities are computed for the event conditional upon some events specified by the related factors (predictors).

##### 4.2.1. Joint effects of “Residency” and “Insured”:

This section starts with the first specification, simple but useful for a general public perception, using sub-table BURDEN1 (from Table 1). Results are provided in Table 2, with all coefficients being statistically significant, mostly at any conventional level (p-value<0.001).

Table 2 – Estimation results for probability of distress on “Residency” and “Insured”

	Intercept	Resident	Insured
		No	No
	$\beta_0$	$\beta_1$	$\beta_2$
logit (C A)	-1.1239*** [0.2738] (-4.1046)	2.2628*** [0.3178] (7.1209)	0.9652*** [0.3153] (3.0612)
Logit (B A)	-0.7349*** [0.2516] (-2.9213)	0.5222* [0.3264] (1.5999)	1.0777*** [0.3349] (3.2181)
Residual deviance: 1.45 on 2 degrees of freedom (d.f.); Log-likelihood: -17.92 on 2 d.f. Baseline = no financial burden at all; (s.e) and z-values in parentheses [] and ( ); (***, **, *) denote coefficients significant at 1, 5 and 10%, respectively.			

Rewriting the above empirical results into the following stylized facts, the first two logits are as follows:

$$\ln\left(\frac{\hat{\pi}_C}{\hat{\pi}_A}\right) = -1.1239 + 2.2628NonRes + 0.9652Uninsured$$

$$\ln\left(\frac{\hat{\pi}_B}{\hat{\pi}_A}\right) = -0.7349 + 0.5222NonRes + 1.0777Uninsured$$

These logits enable us to estimate the probability that a patient falls into debt if that patient is nonresident and uninsured (or medical costs are not eligible for reimbursement under the policy)  $\hat{\pi}_C$ :

$$\hat{\pi}_C = \frac{e^{-1.1239+2.2628+0.9652}}{1 + e^{-1.1239+2.2628+0.9652} + e^{-0.7349+0.5222+1.0777}} = 0.7084$$

And, the probability that a patient falling into some kind of adverse effect (but not indebtedness) having negligible or no insurance  $\hat{\pi}_B$  while being non-resident:

$$\hat{\pi}_B = \frac{e^{-0.9283+1.2128+0.7927}}{1 + e^{-0.9462+2.5694+0.7642} + e^{-0.9283+1.2128+0.7927}} = 0.2052$$

Consequently, only 8.64% will not be adversely affected at all if hospitalized without insurance while being non-resident.

#### 4.2.2. Joint effects of “Insurance coverage” and “Residency” on the probability of distress:

In the next estimation, we model the probability of falling into a specific category of post-treatment “financial position”, conditional upon levels of insurance reimbursement and residency status of patients, based on data set BURDEN3. Results are provided in Table 3.

Table 3 – Modeling probability of financial distress upon “Residency” and “Insurance coverage”

	Intercept	Resident	InsL2		
			No	Lo	Med
	$\beta_0$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
Logit (C A)	-0.9279*** (-2.9276)	2.3381*** (7.2249)	-0.52045 (-1.0214)	-0.6714 (-1.4535)	0.7144** (1.9899)
Logit (B A)	-0.6466** (-2.0658)	0.5808* (1.7572)	-0.0468 (-0.0858)	-0.5458 (-1.0113)	0.9368** (2.4390)

Baseline = no financial burden at all; z-values in parentheses; (\*\*\*, \*\*, \*) denote coefficients significant at 1, 5 and 10% respectively. Residual deviance: 17.31636 on 6 degrees of freedom; Log-likelihood: -35.4262 on 6 degrees of freedom.

As these model the probabilities of falling into burden category C (and B) vs. category A (zero adverse effect of health expenditure), depending on whether a patient is “non-resident” and “uninsured”. The results show very clear trend. Both burdens of categories C (distressed) and B (partly adversely affected) show significantly negative effects of being nonresident and having no insurance on the probability of becoming indebted for patients. In other words, having no insurance and being non-resident increases the log-odds of falling into type C or B of burden.

To measure the risk, using results from Table 3, take the category C (probability of falling into debt) as example. The “Non-residency” factor has shown a much larger (negative) effect on the probability of a patient to become indebted than being uninsured, with the significant coefficient being +2.388, compared to 0.7144 for “being uninsured”.

$$\ln\left(\frac{\hat{\pi}_C}{\hat{\pi}_A}\right) = -0.9279 + 2.3881NonRes - 0.5204InsLow - 0.6714InsMed + 0.7144InsNil$$

$$\ln\left(\frac{\hat{\pi}_B}{\hat{\pi}_A}\right) = -0.6466 + 0.5808NonRes - 0.0468InsLow - 0.5458InsMed + 0.9368InsNil$$

It is then possible to compute the probability that a nonresident patient falling into debt having no insurance  $\hat{\pi}_C$ :

$$\hat{\pi}_C = \frac{e^{-0.9279+2.3881+0.7144}}{1 + e^{-0.9279+2.3881+0.7144} + e^{-0.6466+0.5808+0.9368}} = 0.6945$$

The probability of a patient without insurance and coming from other region to become indebted is quite high, almost 70%. In addition, the probability that a nonresident patient falling into some kind of adverse effect—but not indebtedness—having no insurance ( $\hat{\pi}_B$ ) is much lower, roughly 25%:

$$\hat{\pi}_B = \frac{e^{-0.6466+0.5808+0.9368}}{1 + e^{-0.9279+2.3881+0.7144} + e^{-0.6466+0.5808+0.9368}} = 0.2534$$

Only 5.2% will not be adversely affected at all if hospitalized without insurance while being nonresident.

#### 4.2.3. The effects of “Health Cost” and “Insurance”:

Next, we consider probabilities of falling into different financial positions (A=Strong, B=Adversely Affected, or C=Indebted/Destitute) conditional upon levels of average cost of treatment and insurance reimbursements (sub-table BURDEN4). Baseline category for this regression is probability of no negative financial effect at all, and two reference categories for AvgCost and Insurance Level are LowCost and High reimbursement, respectively.

Table 4 – Modeling categories of financial burden following average cost and insurance levels

		AvgCost		Insurance Level	
		HiCost	MedCost	Med	Neg
	$\beta_0$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
Logit (C A)	-0.9462** (-2.5037)	2.5694*** (5.1764)	1.2158*** (3.3389)	-0.1436 (-0.3233)	0.7642** (2.3656)
Logit (B A)	-0.9283** (-2.3424)	1.2128** (2.2110)	0.5020 (1.3182)	-0.3656 (-0.6778)	0.7927** (2.1660)
Residual deviance: 5.72 on 8 d.f.; Log-likelihood: -32.19 on 8 d.f. z-value in brackets. Baseline category: No financial burden after staying in hospital. (***, **, *) denote coefficients significant at 1, 5 and 10% respectively.					

From Table 4, most coefficients are statistically significant, except only one categorical variable of “Medium Insurance” coverage, with  $\beta_3$  being insignificant. Stylized facts from Table 4 results are rewritten as:

$$\ln\left(\frac{\hat{\pi}_C}{\hat{\pi}_A}\right) = -0.9462 + 2.5694HiCost + 1.2158MedCost - 0.1436InsMed + 0.7642InsNeg$$

$$\ln\left(\frac{\hat{\pi}_B}{\hat{\pi}_A}\right) = -0.9283 + 1.2128HiCost + 0.5020MedCost - 0.3656InsMed + 0.7927InsNeg$$

These can be converted to the probability that a patient falling into debt having negligible insurance benefits while paying high health care cost ( $\hat{\pi}_C$ ):

$$\hat{\pi}_C = \frac{e^{-0.9462+2.5694+0.7642}}{1 + e^{-0.9462+2.5694+0.7642} + e^{-0.9283+1.2128+0.7927}} = 0.6912$$

And, the probability that a patient falling into some kind of adverse effect (but not indebtedness) having negligible or no insurance  $\hat{\pi}_B$  while paying higher cost of services:

$$\hat{\pi}_B = \frac{e^{-0.9283+1.2128+0.7927}}{1 + e^{-0.9462+2.5694+0.7642} + e^{-0.9283+1.2128+0.7927}} = 0.2645$$

Only 4.43% will not be adversely affected at all if hospitalized without insurance while paying higher costs. From results of Table 4 and 5, it is safe to state that basically the joint effect of “non-residency” + “uninsured” has similar impact on risk of destitution (and hardship) to the joint effect “receiving negligible benefits” + “high costs of health services”.

#### 4.2.4. Treatment outcome, health care cost and severity of illness:

Next analysis focuses on probabilities of “Treatment Outcome” for patients, conditional upon average cost of services and severity of illness, employing the END2 subset of Table 1. Estimated coefficients are provided in Table 5, following which it is clear that all are highly significant, in fact at any conventional level for all, except only  $\beta_4$  of Logit(C|A).

Table 5 – Modeling “Treatment Outcome” following cost levels and illness

	Illness			Average Cost of Services	
	Intercept	Bad	Emergency	High	Medium
	$\beta_0$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
Logit (C A)	-4.5965*** (-4.9401)	2.3444*** (2.9511)	4.1486*** (5.0950)	3.2568*** (4.0096)	1.2881* (1.8532)
Logit (B A)	-1.1231*** (-3.5675)	1.1452*** (3.8388)	1.1074*** (2.6608)	2.4116*** (4.6114)	1.0800*** (3.2739)
Residual deviance: 14.36 on 8 d.f.; Log-likelihood: -32.17 on 8 d.f. z-value in brackets. Baseline category: Complete recovery after treatments. (**, **, *) denote coefficients significant at 1, 5 and 10% respectively.					

Table 6 results are rewritten in equation forms as follows:

$$\ln\left(\frac{\hat{\pi}_C}{\hat{\pi}_A}\right) = -4.5965 + 2.3444Bad + 4.1486Emergency + 3.2568HighCost + 1.2881MedCost$$

$$\ln\left(\frac{\hat{\pi}_B}{\hat{\pi}_A}\right) = -1.1231 + 1.1452Bad + 1.1074Emergency + 2.4116HighCost + 1.08MedCost$$

The results tell that the probability that a patient quits while in condition of “serious illness” and anticipating high cost of treatments ( $\hat{\pi}_C$ ) is quite a high risk, 58%:

$$\hat{\pi}_C = \frac{e^{-4.5965+4.1486+3.2568}}{1 + e^{-4.5965+4.1486+3.2568} + e^{-1.1231+1.1074+2.4116}} = 0.5805$$

Likewise, the probability that a patient can only be partially cured  $\hat{\pi}_B$  while suffering high cost of services is also high, over 38%:

$$\hat{\pi}_B = \frac{e^{-1.1231+1.1074+2.4116}}{1 + e^{-4.5965+4.1486+3.2568} + e^{-1.1231+1.1074+2.4116}} = 0.3845$$

In the estimated  $\hat{\pi}_C$ , both conditions of illness and high costs have large impact on increasing the risk of early quitting. However, in case of  $\hat{\pi}_B$  costliness of treatment appears to be more determining.

These two high probabilities lead to the fact that the probability of full recovery for a patient hospitalized in emergency, anticipating higher costs of treatment, is very low, just 3.5%.

#### 4.2.5. On the sensitive issue of “thank-you” OOP:

Finally, estimation results are reported based on data provided in ENV2 sub-table, which model probability of a patient paying high or medium “extra thank-you money” conditional upon income ranks and/or severity of illness. The baseline category is “paying negligible thank-you” for response variable. For “Ill2” the reference category is “light sickness” and for “Income Rank”, the reference “Medium”.

Table 6 – Modeling “Thank-you OOP” against “Illness” and “Income Rank”

		Illness		Income Rank	
		Bad	Emergency	High	Low
	$\beta_0$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$
Logit (HiPay Neg)	0.5079 [0.5813] (0.8737)	-1.7684*** [0.4560] (-3.8778)	-1.4804*** [0.4851] (-3.0520)	-0.5079 [0.6657] (-0.7629)	-0.9134* [0.4835] (-1.8891)
Logit (MedPay Neg)	0.6104 [0.5128] (1.1902)	-1.0751*** 0.41346 (-2.6003)	-1.4605*** [0.4880] (-2.9930)	-0.9899 [0.6265] (-1.5799)	-1.0804*** [0.3933] (-2.7471)
Residual deviance: 3.81 on 2 d.f.; Log-likelihood: -24.11 on 2 d.f.					
[s.e.] in square bracket and (z-value) in parentheses. Baseline category: Pay negligible “extra envelop” amount; (**, *,) denote coefficients significant at 1, 5 and 10% respectively.					

Clearly, the estimated results in Table 6 show that both income ranks of category Low (of “Income Rank”) and both Bad and Emergency (of “Illness”) jointly reduce the probability of patients paying “thank-you money” from medium to high level. That is, these lower-income patients when faced with serious illness or emergency are less likely to afford significant “OOP” payment.

$$\ln\left(\frac{\hat{\pi}_{HiPay}}{\hat{\pi}_{NegPay}}\right) = +0.5079 - 1.7684Bad - 1.4804Emerg - 0.5079HiInc - 0.9134LowInc$$

$$\ln\left(\frac{\hat{\pi}_{MedPay}}{\hat{\pi}_{NegPay}}\right) = +0.6104 - 1.0751Bad - 1.4605Emerg - 0.9899HiInc - 1.0804LowInc$$

Still, the poor “emergency” are willing to make expensive “thank-you” OOP payment with a probability ( $\hat{\pi}_{HiPay}$ ) of 7.8% following the above estimation:

$$\hat{\pi}_{HiPay} = \frac{e^{-1.4804-0.9134}}{1 + e^{-1.4804-0.9134} + e^{-1.4605-1.0804}} = 0.0780$$

Likewise,  $\hat{\pi}_{MedPay}$  is estimated at ~6.7%:

$$\hat{\pi}_{MedPay} = \frac{e^{-1.4605-1.0804}}{1 + e^{-1.4804-0.9134} + e^{-1.4605-1.0804}} = 0.0673$$

After all, we reach a high probability, 85.46%, that low-income patients in emergency can only afford negligible amount of “thank-you” OOP payment.

## 6. Discussion and conclusions

For patients, risk increases when patients are either uninsured or not eligible to a “reasonable” coverage. Uninsured and nonresident patients are most vulnerable to destitution. The estimated probability of falling into hardship for these patients is very high, ~70% (4.2.1).

In addition, as shown in Tables 3 and 4, our stylized facts lead to a useful insight that the joint effect of “non-residency” and “uninsured” is similar to the effect “receiving negligible benefits” and “high costs of health services”, as to the risk of destitution of hospitalized patients, with the probability estimated at approx. 70% (4.2.2-3). In addition, the probability for seriously sick patients to stop treatment facing high health cost is also very high, above 58% (following Table 5, 4.2.4).

The above probabilities show that the risk runs very high for a large group of patients. With probability of 70%, it is highly probable that for every three uninsured and nonresident patients hospitalized, two are subjected serious financial hardship or destitution. From the other result, for every two patients hospitalized in serious illness which requires costly treatment, it is highly likely that at least one would face the risk of destitution. Although Vietnamese and experienced researchers would say the risk is high, earnest effort to address the issue of “how high is high” is needed to provide the public and policy-makers with more insightful answers. These probabilities unveil the reality that Vietnamese patients are more vulnerable to the risk of destitution than previously thought of.

Looking closely into factors contributing to increase the probabilities of destitution in above estimations, the main “culprits” are:

- Nonresidency of patients. This at least implies two issues: travel costs, and asymmetric information.
- High costs of treatment, including equipment, drugs, care and room.
- Inadequate actual insurance coverage. Although in theory, most patients with Vietnamese UC are entitled to 80% to 100% coverage, the practices clearly have not been reflecting that range. The empirical data show that the majority of patients are reimbursed less than 50% of actual expenditure.

Also, in a rather “sensitive” issue of “thank-you money” the majority of surveyed patients spent less than 5% of expenditure for this OOP payment. This fact suggest that the issue is more symbolic than substantial in the issue of destitution. In fact, more than 85% of patients from lower SES families—who are seriously ill and anticipate costly treatment—pay negligible “thank-you money” during their hospital stay.

As the amended Law on Health Insurance shortly comes into effect, the ambitious plan of aiming at 100% UC and all Vietnamese having health insurance is apparently facing a dilemma. While the current statistics show that roughly 60% of Vietnamese holding UC, the majority of insured patients could hardly be financed adequately by insurance, see Figures (2.a) and (2.b). Guess what would happen if this current level of 60% insured increases to 100%, it is likely that actual coverage range would tend to go down. If this decrease would lead to higher rate of “negligible insurance”, the computed probabilities would enable us to predict that the probability of falling into destitution may even rise. In fact, before the introduction of the new law, tension already ran high at times in 2013-4 period upon news on possible collapse of Vietnam Health Insurance Fund, causing deep concerns in the society. This says, without an appropriate evidence-based policy making process, an initially nice idea may end up penalizing the poor, eventually.

In addition, asymmetric information and lack of alternative financing should be seriously taken into account, too. From actual survey and analysis, it becomes evident that a large portion of health care expenditure has been caused by the problem of asymmetric information, exacerbated by poor patients’ borrowings, especially in the current situation of Vietnam where “loan sharks” are rampant and frequently visited by poor patients/households.

Finally, although the modeling using specifications of polytomous logistic models has proven to be satisfactory and provided useful insights, the existing data set, containing data from 330 interviews, is still small. This size limits the possibility for us to measure other likely influential and meaningful factors. An expanded data set, of about 1,000 cases, would enable the incorporating of additional explanatory variables into more complex models, promising further, and perhaps better, insights for the future policy making process.

## References

Agresti, A. (2002). *Categorical Data Analysis*. Hoboken, NJ: John Wiley & Sons.

Bloom, G. (1997). Primary health care meets the market: lessons from China and Vietnam. IDS Working Paper 53, University of Sussex, UK.

Chaudhuri, A., & Roy, K. (2008). Changes in out-of-pocket payments for healthcare in Vietnam and its impact on equity in payments, 1992–2002. *Health Policy*, 88(1), 38-48.

Dan Tri Online (2014, Dec 15). Hon 47 trieu dong den nguoi me tre bi u nao [More than 47 million dong for young mom with brain tumor]. <http://dantri.com.vn/tam-long-nhan-ai/trao-hon-47-trieu-dong-den-nguoi-me-tre-bi-u-nao-5-lan-danh-roi-con-1008768.htm>, accessed Dec 17, 2014.

Dao, H. T., Waters, H., & Le, Q. V. (2008). User fees and health service utilization in Vietnam: How to protect the poor?. *Public Health*, 122(10), 1068-1078.

Ensor, T. (2004). Informal payments for health care in transition economies. *Social Science & Medicine*, 58(2), 237-246.

Ekman, B., Liem, N. T., Duc, H. A., & Axelson, H. (2008). Health insurance reform in Vietnam: a review of recent developments and future challenges. *Health Policy and Planning*, 23(4), 252-263.

Ha, N. T. H., Berman, P., & Larsen, U. (2002). Household utilization and expenditure on private and public health services in Vietnam. *Health Policy and Planning*, 17(1), 61-70.

Liu, X., Tang, S., Yu, B., Phuong, N. K., Yan, F., Thien, D. D., & Tolhurst, R. (2012). Can rural health insurance improve equity in health care utilization? A comparison between China and Vietnam. *International Journal of Equity in Health*, 11:10.

Lönnroth, K., Tran, T. U., Thuong, L. M., Quy, H. T., & Diwan, V. (2001). Can I afford free treatment?: Perceived consequences of health care provider choices among people with tuberculosis in Ho Chi Minh City, Vietnam. *Social Science & Medicine*, 52(6), 935-948.

Russell, S. (2004). The economic burden of illness for households in developing countries: a review of studies focusing on malaria, tuberculosis, and human immunodeficiency virus/acquired immunodeficiency syndrome. *The American Journal of Tropical Medicine and Hygiene*, 71(2), 147-155.

Segall, M., Tipping, G., Lucas, H., Dung, T. V., Tam, N. T., Vinh, D. X., & Huong, D. L. (2002). Economic transition should come with a health warning: the case of Vietnam. *Journal of Epidemiology and Community Health*, 56(7), 497-505.

Septhri, A., Chernomas, R., & Akram-Lodhi, A. H. (2003). If they get sick, they are in trouble: health care restructuring, user charges, and equity in Vietnam. *International Journal of Health Services*, 33(1), 137-161.

Septhri, A., Chernomas, R., & Akram-Lodhi, H. (2005). Penalizing patients and rewarding providers: user charges and health care utilization in Vietnam. *Health Policy and Planning*, 20(2), 90-99.

Thuan, N. T., Lofgren, C., Lindholm, L., & Chuc, N. T. (2008). Choice of healthcare provider following reform in Vietnam. *BMC Health Services Research*, 8:162.

Van Doorslaer, E., O'Donnell, O., Rannan-Eliya, R. P., Somanathan, A., Adhikari, S. R., Garg, C. C., ... & Zhao, Y. (2006). Effect of payments for health care on poverty estimates in 11 countries in Asia: an analysis of household survey data. *The Lancet*, 368(9544), 1357-1364.

Van Doorslaer, E., O'Donnell, O., Rannan-Eliya, R. P., Somanathan, A., Adhikari, S. R., Garg, C. C., ... & Zhao, Y. (2007). Catastrophic payments for health care in Asia. *Health Economics*, 16(11), 1159-1184.

Whitehead, M., Dahlgren, G., & Evans, T. (2001). Equity and health sector reforms: can low-income countries escape the medical poverty trap?. *The Lancet*, 358(9284), 833-836.

Xu, K., Evans, D. B., Carrin, G., Aguilar-Rivera, A. M., Musgrove, P., & Evans, T. (2007). Protecting households from catastrophic health spending. *Health Affairs*, 26(4), 972-983.

## Appendixes

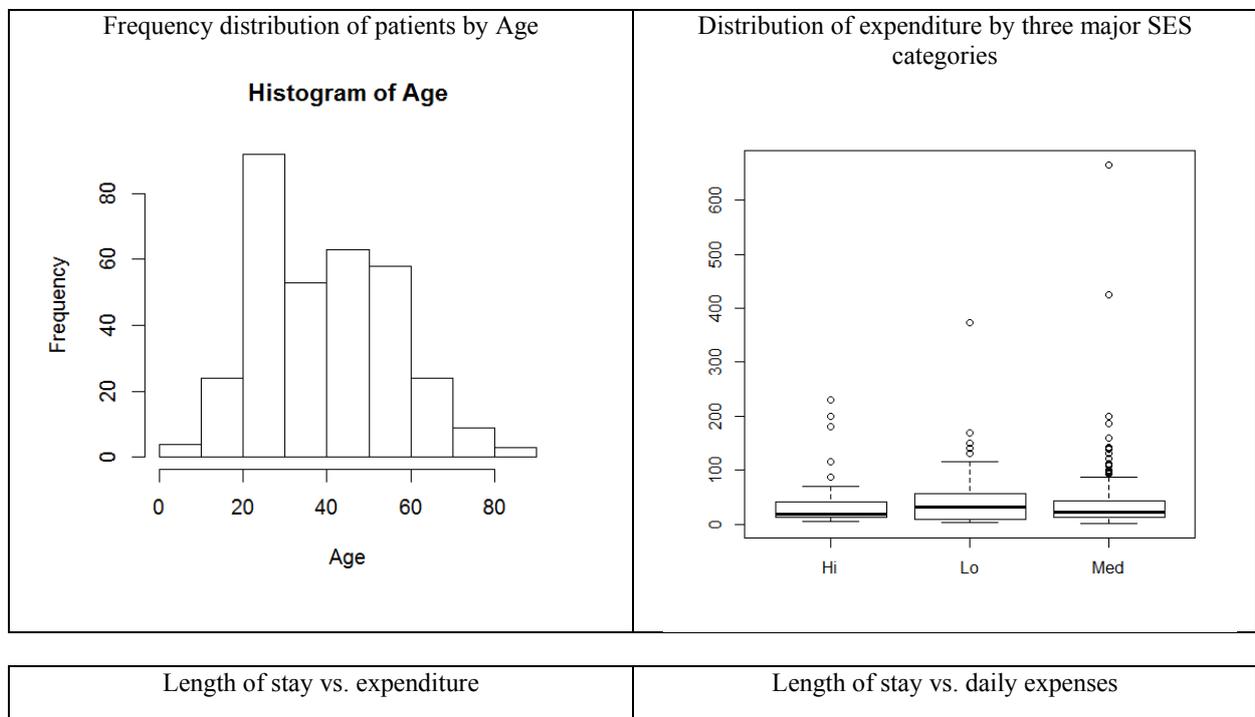
### A1. Reading data set into the R system

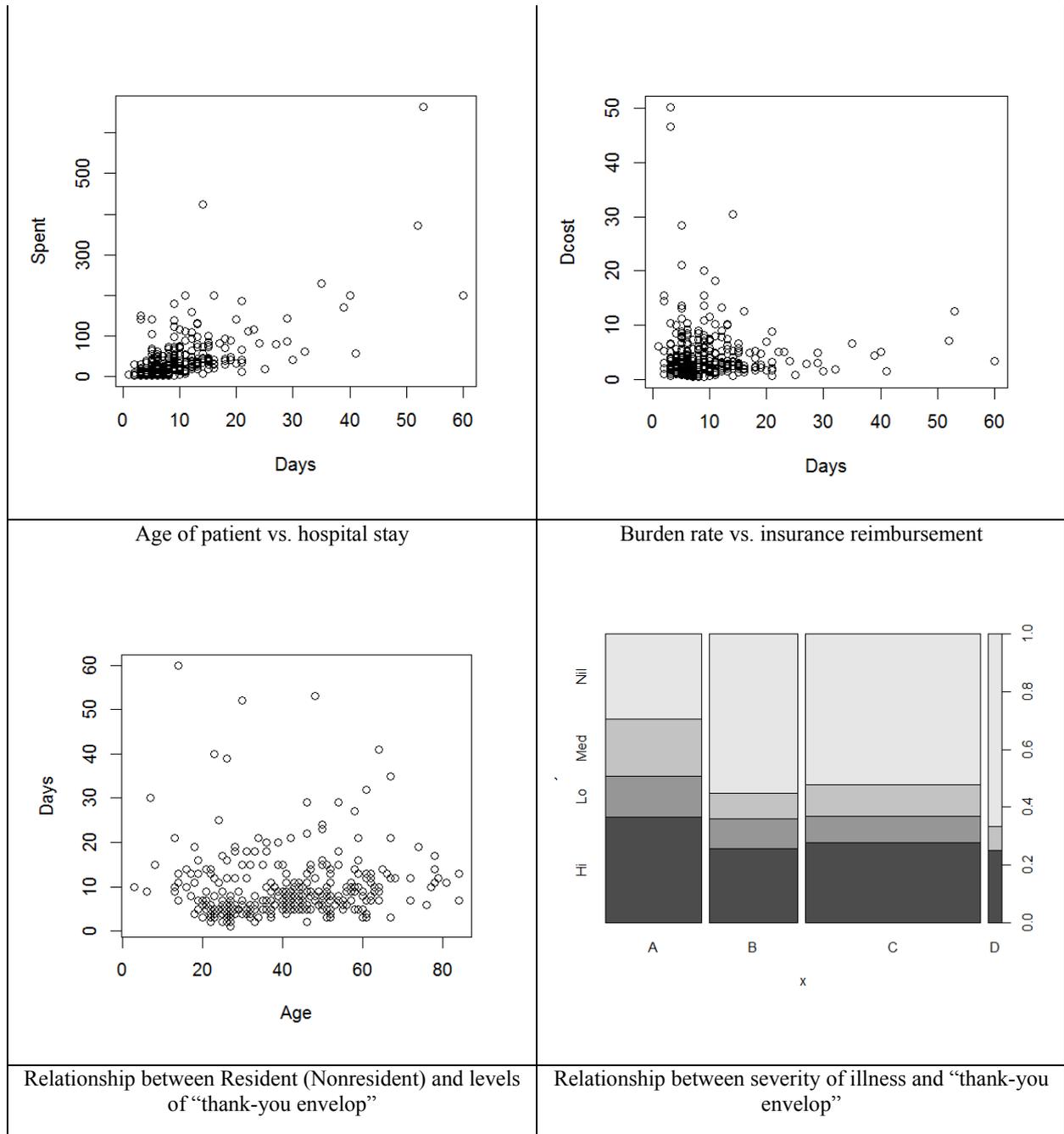
Factor	Basic description	Characteristics	Remark for later use
ID	Coded number for each patient	Each patient has a unique code.	This will only be used to produced graphs where needed.
Name	Name of patient	Those who refuse to allow the use of their true name will be replaced by N.A. Some patients may have identical names, and they will be distinguished by ID.	This will not be used.
Res	This answers if the patient is resident of the region where the hospital is located.	This takes binary value of Yes or No.	This has a potential value for implying transports and related costs for patient's relatives.
Days	Number of days the patient spent in the hospital.	Quantitative variable.	This is for charting the frequency distribution and transforming into long or short stay.
Stay	A dummy variable to define if length of stay in hospital by a patient is short or longer.	This takes value of S if one's stay is less than 10 days, and L (longer) if 10 days or longer.	This is potentially a good candidate for a binary predictor variable.
Insured	Whether a patient has a valid health insurance policy.	This variable is binary and takes value of "Yes" or "No".	This is potentially a good candidate for a binary predictor variable.
MaxIns	The maximum level of coverage by insurance policy if the patient has one.	Quantitative factor, measured by percentage of total "eligible costs" according to regulations.	This is supplementary information only.
Edu	Highest level of education	Values: JHS: Junior High HS: High School Uni: College/University Grad: Graduate School	This is supplementary information only.
SES	Socio-economic status	This is a multicategory variable, taking values of: High, Medium, Low.	This is potentially a good candidate for a multi-categorical predictor variable.
Illness	Degree of severity of illness or injury when hospitalized.	This is a multicategory variable, taking values of: Emergency, Bad, Ill and Light.	This is potentially a good candidate for a multi-categorical predictor variable. Ill and Light categories can also be grouped into one single category, in which case we have a transformed factor of Ill2 (also in the data set).
Jcond	Status of job	This takes value of Good, Stable, Unstable,	This is supplementary information only.

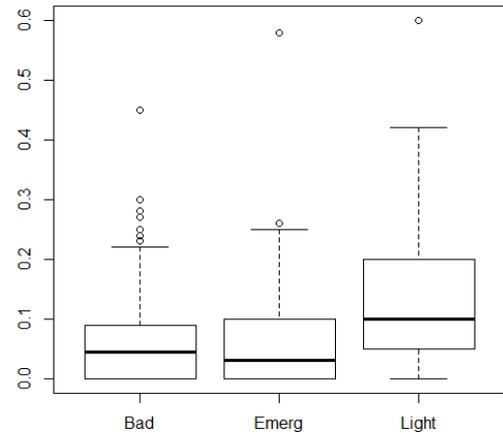
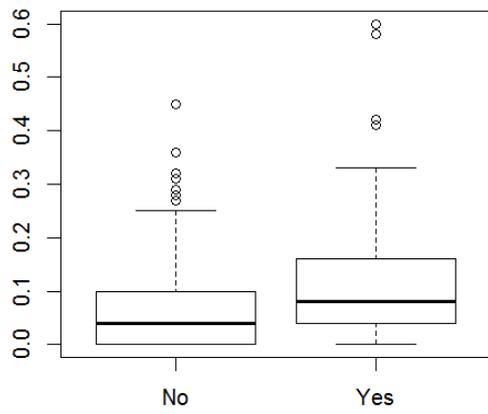
		Unemployed or N.A. (i.e. Others: retired, high school students)	
Income	Annual income in millions of Vietnamese Dong. Current exchange rate: \$1=VND21,200 (as of Dec 1, 2014).	Quantitative factor. The factor can be continuous in theory, but is mostly categorical in practice.	This will be used to derive the IncRank variable.
IncRank	Rankings of income of a patient.	This takes value of High, Middle, or Low.	This is potentially a good candidate for a multi-categorical predictor variable.
Spent	Total money spent during his/her stay in hospital in millions of Vietnamese Dong. Using official exchange rate, VND 1 million is equivalent to \$47.2.	Quantitative variable.	
Dcost	Average daily cost the patient had to pay during treatment period.	Quantitative variable.	
Pins; Pinc; Pchar; Ploan	Portions of finance from sources: Insurance reimbursement, Income, Charity funds from civil organizations or employers, or Borrowings.	Quantitative variables. They are measure in percentage of total costs the patient had to cover.	
InsL2	Ranked levels of actual insurance reimbursement for patients who have policies.	It takes value of High, Medium, or Low if a patient has an insurance policy. It takes Nil if the patient is not insured at all.	For actual transformation when necessary both Low and Nil can be grouped into one category of Neg (i.e., negligible).
Streat, Srel, Senv	Percentage of funds used for the purpose of main treatments, for covering costs of relatives coming to help the patient, or paying extra “thank-you envelop” or bribing doctors/staff.	These are quantitative variables, taking value of percentage. For instance, Patient ID001 has {89%;4%;7%}={0.89; 0.04; 0.07}. Streat+Srel+Senv = 100%.	Only Senv can be a potential candidate for modeling as dependent categorical variable, after being transformed into levels of “extra fees”, taking value of High, Medium, or Low. That newly derived categorical variable is called EnvL and also appears in the data set.
Burden	Patient’s and family’s self-evaluation of their financial position after paying health care costs.	This is a multi-category variable, taking value of A (strong; no adverse affect at all); B (affected but not the worrying level); C (seriously affected) and D (destitute / “bankrupt”).	This represents a group of critically important categories that the study employs to learn about what factors likely affect the probabilities of falling into each category of financial burden.
End	The health status after treatment.	This is a group of multi-categorical variables,	This represents a group of critically important

		taking values of A (complete recovery), B (partial recovery, needing post-treatment follow-ups), C (stopped whilst being treated), or D (quit early).	categories that the study wants to model to know what factors affect the probabilities of falling into each category of treatment completion after patients' stay in hospital.
IfHigher	Self-evaluation of patient and family about financial status if the patient continues to be hospitalized next time.	This takes the same values as "Burden" factor.	This can potentially be a candidate for future examination, especially when a larger sample is available. It is not used for this analysis.

A2. Supplementary graphs for visualization of data set.







Distribution of Income level in relationship to burden after treatment

Distribution of Spent level in relationship to burden after treatment

