HEDG Working Paper 05/06

Panel data analysis of dentists' activity under global budgeting in the presence of activity-related non-response

Miaw-Chwen Lee
Andrew M Jones

October 2005

ISSN 1751-1976

york.ac.uk/res/herc/hedgwp

Panel data analysis of dentists' activity under global budgeting in the presence of activity-related non-response

MIAW-CHWEN LEE* AND ANDREW M. JONES ¶,†

* *Department of Social Welfare, National Chung Cheng University, Taiwan*
E-mail: mclee@sw.ccu.edu.tw

† *Department of Economics and Related Studies, University of York, U.K.*
E-mail: amj1@york.ac.uk

Summary This paper evaluates the impact of the introduction of global budgeting on dentists' activity in Taiwan using a unique and rich panel dataset that was created specifically for the task. The panel data for 4424 dentists over 48 months, January 1997 to December 2000, was drawn from the BNHI's data warehouse. The dataset has approximately 66% of dentists who are not observed over all periods. The paper examines the existence and consequences of unit non-response on estimates of the response of dentists' activity to the introduction of global budgeting. It is based on the framework of selection on observables. We apply three techniques to assess the existence and magnitude of non-response bias: (1) probit models for non-response (2) variable addition tests (3) inverse probability weighting. The results show evidence of activity-related non-response. Non-response is concentrated among dentists with lower and unstable daily numbers of visits and with higher income. Non-response has substantial influence on the estimates of the mix of services provided to patients. The empirical results shed light on the emergence of a two-tier dental care system due to the introduction of global budgeting.

JEL classification: I11, C33

Keywords: *Dental care, global budgeting, unit non-response, attrition, panel data, selection on observables, inverse probability weighting, Taiwan*

¶**Address correspondence to**: Professor Andrew M. Jones, Department of Economics and Related Studies, University of York, York, YO10 5DD, U.K.; Tel: +44-1904-433766; Fax: +44-1904-433759; E-mail: amj1@york.ac.uk

1. INTRODUCTION

Dental care is a branch of medicine that has distinctive characteristics; these include the limited numbers of diseases, the predictability and ease of diagnosis, the limited range of treatments available, and the availability of cost-effective preventive care (Sintonen and Linnosmaa, 2000). These characteristics made it convenient for the Taiwanese Bureau of National Health Insurance (BNHI) to introduce global budgets for dental care prior to introducing them for Western medicine in general. The introduction of global budgeting in July 1998 did not change the payment basis for individual dentists, they are still paid by fee-for-service, but the price of each service is adjusted according to the ex-post total quantity of services provided. The intention is that global budgeting should create economic incentives to encourage co-operative efforts and group responsibility for controlling the cost and the quality of care, while preserving professional autonomy.

Panel data analysis is often used to examine policy effects, due to the scope for controlling for individual heterogeneity. However, using panel data raises the problem of sample attrition bias, when non-response is related to the outcome of interest. This paper evaluates the impact of global budgeting on dentists' activity using a unique and rich panel dataset that was created specifically for the task. The panel data for 4424 dentists over 48 months, January 1997 to December 2000, was drawn from the BNHI's data warehouse (Lee and Jones, 2004). The data was collected by proportional stratified random sampling matching the ratio of numbers of dental care institutions to the population in six regions. We randomly sampled 2,000 dental care institutions (including clinics and hospitals) out of about 5,000 in the population. The base-line month of sampling is December of 1998 corresponding to the 24th wave of the data rather than the first wave. This means that the panel is rather unusual and the data contain complex patterns of non-response. The data is an unbalanced panel and the observed number of dentists for the whole period is 4424. Individual dentists observed at the first wave (January 1997) may drop out in any subsequent wave and new dentists may be added, some dentists might re-enter the sample after leaving. The number of dentists in the first wave is not the maximum over the 48 months.

Despite a 66% non-response rate in the panel, using the unbalanced panel does not necessarily bias estimates of the parameters of interest, if non-response is random and independent of dentists' activity (Diggle and Kenward, 1994). However, it is likely that non-response is non-random. That is, non-response probabilities are likely to be associated with dentists' activities. For example, contracting with the BNHI may involve self-selection by dentists; dentists who have a low percentage of insured patients are more likely to quit the NHI system and become fully private practitioners. Despite the fact that the panel data fixed effects estimators used in our analysis are consistent if non-response is time invariant (Wooldridge, 2002b p.578), it is worthwhile investigating the nature and potential consequences of non-response. Dealing with non-response in a long panel, with 48 periods, is of particular interest.

The first question concerns the effect of non-response on the generalisability of the research findings. What are the characteristics of those who leave and those who stay in the sample? The second question relates to the consequences of activity-related non-response and whether non-response generates bias in regression estimates. The non-response problem is usually recognized as a problem of selection bias in the econometrics literature. Sample selection bias has been paid considerable attention in the econometrics literature since Heckman's (1976, 1979) and Hausman and Wise's (1979) work on estimating models with sample selection bias. They examine selection bias by focusing on selection equations, which regress indicators of non-response on exogenous variables. But in social science research, it is often difficult to find appropriate exogenous variables that are related to the probability of selection and which do not have a direct effect in the main outcome equation.

Verbeek and Nijman (1995) and Fitzgerald, Gottschalk, and Moffitt (1998) raise the distinction between selection on observables and selection on unobservables. We analyse non-response using the concept of selection on observables, in which non-response is correlated to observable endogenous variables. Subsequently, we apply inverse probability weighting, proposed by Robins *et al.* (1995), Fitzgerald *et al.* (1998) and Wooldridge (2002b), to adjust for non-response in the estimation of the two-way fixed effects panel data model for dentist activity.

The purposes of this paper are therefore to examine, firstly, the existence of a non-response problem. Secondly, if a non-response problem exists, whether it leads to biased or inconsistent estimates in dentists' activity equations. The paper is organized as follows. Section 2 reviews statistical aspects of the non-response problem, especially the concept of selection on observables. Section 3 introduces the policy context and the incentives that influence dentists' behaviour in Taiwan. Section 4 presents the descriptive analysis and determinants of the probability of non-response that contribute to the subsequent construction of selection probability models. Section 5 presents the empirical models and Section 6 discusses the results. Conclusions and policy implications are discussed in Section 7. The main contribution of the paper is the development of alternative identification strategies for models of selection on observables in the fixed effects panel data framework, these are different from past empirical work due to the availability of a long panel with complex patterns of non-response.

2. STATISTICAL ISSUES

2.1 Non-response and sample attrition

Using panel data raises the sample non-response problem. When the process of non-response is related to the outcome of interest there is an identification problem and the observed sample no longer represents the population (Manski, 1989; Heckman, 2001). In longitudinal analysis, the key question is whether those who enter, those who leave and those who stay in the panel differ systematically. If they differ then the relevant analyses are potentially biased. The statistical literature classifies three types of non-response: *completely random, random, and informative non-response* (Little and Rubin, 1987; Diggle and Kenward, 1994; Fitzmaurice *et al.*, 1996). With *completely random non-response*, the non-response is independent of both observed and unobserved data. We can say that the density function of the sample with non-response coincides with that without non-response, conditional on observed variables. Estimation with completely random non-response can use standard methods of analysis, although there may be a substantial loss of efficiency due to loss of observations in the incomplete panel. Using S as an indicator of response and y and x as the activity and covariates of interests, completely random non-response is defined by $P(S=1|y,x)=P(S=1)$.

With *random or ignorable non-response*, the non-response is independent of the outcome of interest, conditional on the observables. This is defined by $P(S=1|y,x)=P(S=1|x)$. Fitzgerald et al (1998) and Moffitt *et al.* (1999) extend the definition by proposing *"selection on observables"*, which requires an additional set of observables, z, that are observed in the sample but not included in the activity regression model. These observable variables are selected to be *endogenous* to *y*. The definition can be thus written as an ignorability condition, $P(S=1 \lfloor y,x,z)=P(S=1 | x,z)$[1].

The third type is informative non-response. This is often referred to as *non-ignorable or unobservable non-response*, because the non-response depends on *unobserved* measurements. Consistent estimates can be obtained by predicting the probability of non-response using *exogenous instruments*. That is, the instruments satisfy an exclusion restriction, that they do not have a direct effect on the outcome of interest. This approach has been paid considerable attention in the econometrics literature since Heckman's (1976, 1979) and Hausman and Wise's (1979) work on estimating models with sample selection bias. However, in this analysis it is difficult to find appropriate exogenous variables that are related to the probability of non-response and that can be excluded from the dentist's activity equations[2]. So the empirical analysis for the non-response problem in this paper will focus on the selection on observables approach.

2.2 Selection on observables

A key requirement of the selection on observables approach is that the explanatory variables in the non-response equation, say *z*, not only affect non-response propensities, but also that *z* is endogenous to *y* (see Rotnitzky and Robins, 1997 and Fitzgerald *et al.*, 1998) . The main intention in dealing with selection on observables is to obtain correct estimates of parameters associated with $E(y|x)$, where we do not wish to condition on *z*. That is, the interest focuses on $E(y|x)$ not $E(y|x,z)$. Since the non-response is correlated with the outcome of interestthrough *z*, failure to condition on *z*, would generate inconsistent estimates of $E(y|x)$. However, by including *z* as a regressor, the regression for *y* will also generate "biased" estimates, because *z* is an endogenous variable, which distorts the conditional distribution of *y* on *x*. Following Robins *et al.* (1995), Fitzgerald *et al.* (1998), Moffitt *et al.* (1999), and Wooldridge (2002b), the complete population density, $f(y|\mathrm{x})$, can be derived by weighting observations by the normalised inverse

[1] This specification implies that *x* is observed even though *y* is not. This is the distinction between Moffitt, Fitzgerald, and Gottschalk (1999) and Wooldridge (2002b). Wooldridge uses the ignorability condition $P(S=1|y,x,z)=P(S=1|z)$. This applies when *x* is not observed also when *y* is not observed (Wooldridge, 2002b, p588).

[2] Angrist (1997) has pointed out that in empirical studies it is rare to find an instrument that can be excluded from the equations of primary interest. See also Olsen (1980, 1982), Morz (1987), Diggle and Kenward (1994).

selection probability, *w(z),* based on the conditional independence assumption $P(S=1 | y,x,z)=P(S=1 | z)$, namely by using inverse probability weighting (IPW).

3. DENTISTS' ACTIVITY AND GLOBAL BUDGETING IN TAIWAN

Since the system of National Health Insurance (NHI) was inaugurated in Taiwan in March 1995, covering 96 per cent of the population, the Bureau of National Health Insurance (BNHI) has integrated the role of payer and purchaser. Until July 1998, dental care was reimbursed by a retrospective fee-for-service (FFS) based on an 133-item fee schedule, including consultation fees, X-ray diagnoses, treatments, and operations[3]. From August 1998, dentists agreed to implement a global budget with an eight per cent growth rate per year, regardless of the quantity of services provided[4].

Under the global budget, dentists face uncertainty about theincome they will eventually receive forproviding services. This is because of the system of "*ex-post pricing*". The ex-post price of each service is equal to the unit tariff set in the BNHI's fee schedule multiplied by a "relative point value". The relative point valueequals the ex-ante determined budget cap (E^0) divided by the ex-post *de-facto* expenditure on services provided (E^1)[5]. If actual expenditure E^1 exceeds the target expenditure E^0 the relative point value is less than 1 and the unit price of each service paid to dentists will be reduced proportionately. There is an incentive for dentists to co-operate to decrease the total volume of services provided and avoid this collective sanction.

However, the incentives created by a global budget are somewhat complicated (Benstetter & Wambach, 2001). Dentists may not co-ordinate themselves in a situation with a high relative point value, even if they believe that they will need to work harder in a situation

---

[3] Cosmetic activities, such as dentures and orthodontics, are not included in the fee schedule; they must be paid for by patients' private payments.

4 The growth rate varies every year and is negotiated between the BNHI and dentist associations. See the Q & A of NHI Health Care Cost Arbitration Committee, DOH, Taiwan, 2002. http://www.doh.gov.tw/newverprog/proclaim/list.asp

5 E^1 is equal to the sum of the product of the fee of each service multiplied by its quantity.

with a low point value. A dentist may supply fewer services, because he believes co-operation will achieve a high relative point value, but, at the end of the period, the relative point value may be low and he receives a low or even negative profit, which leads to a high risk of bankruptcy. In contrast, another dentist may believe that there will be a low point value; therefore he supplies a higher volume of services than others. Then he would receive a high profit when there is a high *ex-post* relative point value. It is thus reasonable to assume that dentists may alter their practice behaviour, because they are not able to observe other dentists' behaviour and wish to avoid the risk of bankruptcy. The policy effects of interest are: Did dentists adjust the number of visits or the intensity of care? Did dentists change the mix of services?

We use a two-stage budgeting model to investigate dentists' responses to global budgeting. This model was first applied in Rochaix's (1993) paper on physicians' responses to price-quantity regulation in Quebec. We assume that dentists maximise a utility function that depends positively on their consumption and leisure and is subject to a budget and a time constraint. The total time available is allocated for working and leisure. In the first stage, the decision is how much time to devote to dental practice. A dentist's total activity in region k is a function of the amount of the budget in region k , the supply of dentists in region k, dentists' demographic characteristics, and demand factors. In the second stage, the decision is to choose a particular mix of services. The amount of a particular service provided to patients is influenced by the service's price, other services' prices, and the dentist's total activity.

4. THE DATA

4.1 Sampling and non-response

The Bureau of National Health Insurance (BNHI) is the only payer in the Taiwanese National Health Insurance. More than 90% of health care providers contract with BNHI. The BNHI's payment system has been mainly based on fee-for-service (FFS) since its inauguration in April 1995. Under FFS, the BNHI reimburses the expenditure to contracted providers on a monthly basis, when providers report their detailed claim information to the BNHI in electronic format. This data set is known as the *expenditure claims data*. It is made available through the BNHI data warehouse. There are two levels of expenditure claims database: utilization data per visit or per admission and detailed itemized claims data for treatments. In addition the BNHI holds basic data on the characteristics of contracted health care providers including both institutions and individuals.

The panel data for 4424 dentists over 48 months, January 1997 to December 2000, was drawn from the BNHI's data warehouse. The data was collected by proportional stratified random sampling matching the ratio of numbers of dental care institutions to the population in six regions. We randomly sampled 2,000 dental care institutions (including clinics and hospitals) out of about 5,000 in the population. Then the data on provision of services and characteristics of all dentists in these institutions was extracted[6]. The base-line month of sampling is December of 1998, the 24th month of the 48 months[7]. This means that the panel is rather unusual, with the representative random sample drawn at the 24th month of the 48 months rather than at the first wave. The data contain complex patterns of non-response. The data is an unbalanced panel and the observed number of dentists for the whole period is 4424.

Individual dentists observed at the first wave (January 1997) may drop out in any subsequent wave and new dentists may be added, some dentists might re-enter the sample after leaving. Moreover, we must consider the non-absorbing state of the unbalanced panel in the analyses, since the number of dentists in the first wave is not the maximum over the 48 months. Because of the large proportion of re-entrants, using only a panel based on an absorbing state we may lose important information on the dentists whose non-response and re-entry decisions are based on new policy initiatives, such as global budgeting, which may be correlated to dentists' activities[8]. The number of dentists 'always in' over 48 months is 1527, 34% of 4448 dentists, while 2921 dentists are partial participants ('ever-out').

There are various reasons that dentists may be missing from particular waves of the panel. Some dentists are new entrants, such as those graduating from medical schools. Other dentists transfer into one of the sampled institutions from non-sampled institutions. Some

[6] Robust standard errors are used in all of our regression estimates that allow for clustering of dentists within institutions.

[7] The data was requested in 2001. Because it takes 2-years for data updating and rearrangement, the BNHI suggested that the list of institutions of December 1998 is more comprehensive than more recent months.

[8] This situation is different from the incidental truncation case, in which individuals do not disappear from the panel but certain variables are unobserved for some time periods. In our panel, if dentists attrite we cannot observe all their information in those time periods, except for time-constant characteristics.

dentists quit the NHI system, due to death, retirement, or becoming fully private practitioners. However, that detailed information on the reason for non-response is not available in the data. Potentially all of the kinds of non-response may be activity-related, making the observed sample unrepresentative and creating a source of possible bias. One hypothesis is that non-responders are likely to have higher income than average. This is because dentists who have higher income than average are more likely to provide high fee services that are excluded from the BNHI benefit package, such as dentures and orthodontics. In extreme cases, they may withdraw from the NHI contract and become fully private suppliers. Consequently, the income of dentists observed in the NHI sample is likely to be less than the average of the population. In this analysis, we use the expenditure per day as the measurement of individual dentists' income. This is reasonable because the aggregate expenditure data reflects the amount of income that dentists could derive from providing services to patients. The expenditure data contains information on both quantity and cost of activities. A second hypothesis is derived from the first one: non-responders are likely to have fewer and a more unstable number of visits than the average of the population over time. If the increase in the number of visits can offset the loss of income from providing lower fee services, dentists who remain in the sample are likely to have a higher number of visits than average. Moreover, due to their steady practice behaviour, dentists who stay in the sample are likely to have a more stable numbers of visits over time.

4.2 Measures of activity

Following the literature, measures of the utilization of dental care include the number of dental visits, total expenditure on dental care and the use of specific services (see e.g., Sintonen and Linnosmaa, 2000). The dependent variables are measures of dentists' activity. In this paper, nine separate activities are grouped in two categories. The variables in the first category are proxies of "aggregated activity", including daily number of visits, expenditure per visit, and daily expenditure. The variables in the second category reflect the mix of services provided by dentists, termed "disaggregated services". These include monthly numbers of six separate treatments: amalgam fillings, composite resin fillings, root canal treatment, scaling, extraction, and cleaning[9].

[9] As the global budget was introduced for outpatient dental care only, we focus on the items that could be implemented in outpatient dental care and are in frequent use. The six treatments account

The monthly number of treatments is adjusted by the number of working days in each month[10]. The number of working days per month relies on the civil service calendar decided by the government. In addition, we use expenditure in real terms, which is adjusted by the consumer price index (CPI) at 1996 prices[11].

4.3 Explanatory Variables

The factors influencing dentists' activity include two sorts of variable: time varying and time-invariant. Also, they can be categorised into two types of factor: demand-side and supply-side. The presence of the demand-side variables is to capture the demand effect on dentists' activity as well as control for the variation in patients' characteristics for each dentist. The demand-side time varying variables include average patient age, annual household income, and information on patients' diagnoses. Average patient age is equal to the sum of the age of visiting patients divided by total number of visits per month for each dentist. The annual household income data from the DGBAS[12] (Directorate General of Budget Accounting and Statistics in Taiwan) were weighted by GDP (Gross Domestic Product) at 1996 prices; these are available for the city where dentists practise and vary each year. The proportion of visits in different diagnoses, ICD-9-CM code 520-529, reflects the case-mix of treated patients for each dentist. No time-invariant demand-side variable is included in the study as this is provider-level panel data.

A supply-side time-varying variable, dentist density, is included in the analysis. We define this as the ratio of the number of active practising dentists per 10,000 of the population in the city or county where dentists practise. This varies each year. Apart from the demand inducement model, the purpose of including this variable is to condition on the level of dentist supply in different cities or counties. We use the number of active practising dentists recorded

for 87% of total expenditure and 31% of the total amount for outpatient dental care in 2000, which is calculated using our panel data sample

10 The working hours per week is unobservable for individual dentists, therefore we use published working days per month.

11 The expenditure data adjusted by CPI in this study is appropriate for deflation because: (1) the CPI is one of the factors determining the tariff of services in the fee schedule and/ or the budget; (2) the characteristics of dental care are distinct from medical care, hence we exclude the use of medical care index. A dental care cost index is being developed in Taiwan (NHI health care cost arbitration committee, 2002).

12 Manning et al (1987) found increases in consumer income led to higher utilisation, hence the household income data is included to control for this effect.

by DOH, rather than the number on the registered list. A set of supply-side time-invariant variables includes the dentist's age and gender, the type and ownership of affiliated dental care institutions (hospitals or clinics and private or public) [13], and whether the practice is located in a deprived area or not[14].

In addition we also include monthly time-dummies to control for time effects. This is of particular importance because it captures the timing of the introduction of global budgeting. The time trend represents the month effect on dentists' labour supply over 48 separate months, rather than an average effect between before and after the payment reform. This allows for the policy effects to change over time.

4.4 Descriptive analysis

An important issue here is activity-related non-response. We have nine separate measures of activities. If non-response propensities are related to any measure of dentists' activities, the models using the unbalanced sample may be biased. For the reasons explained above, it is likely that dentists who have missing data are more likely to have a higher proportion of private patients and activities. It is thus possible that dentists who remain in the sample are more likely to have lower expenditure than the average of the population. However, because dentists who remain in the sample serve insured patients, they tend to have more and a stable numbers of visits.

Table 1 shows that the non-response rate over the full 48 months of the panel varies with dentists' characteristics. The overall non-response rate is about 66%. Non-response is greater among female dentists and those who practise in hospitals and in the public sector. There is no significant difference between dentists practising in deprived areas and in non-deprived areas. Non-response rates are also similar between the six branches, though the highest rate, 70%, is in the North branch. Due to the differential non-response rates in dentists'

---

13 Theoretically, dentists could shift their practice institutions, such as between private and public, between clinic and hospital, or between deprived and non-deprived areas. But the empirical data indicates they are constant over time for individual dentists.

14 According to the definition used by the Medical Development Fund in the DOH, a deprived area is a remote area, such as mountain regions; off-islands, such as the islands of Pend-Hu, Machu, and Kinmen; or a town or village where the number of physicians per 3000 of the population is less than 1. In our study, dentists practising in a deprived area are defined as whenever, between 1997 and 2000, dentists have practiced in a defined deprived area.

characteristics, we examine further dentists' characteristics and activities among non-response states. This focuses on whether the characteristics and activities differ between those who were present for all periods and those were not.

Table 1: Non-response rate over 48 months by dentists' characteristics (n=4448)

Characteristics	Non-response rate (%)
Gender	
Male	56.6
Female	76.6
Type of Practice	
Clinic	57.3
Hospital	91.9
Ownership	
Private	61.8
Public	89.7
Location	
Deprived areas	66.6
Non-deprived areas	65.6
Branch	
Taipei	65.9
North	70.2
Central	62.7
South	63.7
Kaoping	65.3
East	69.4

Table 2 shows the mean values and standard errors of dentists' characteristics and activities by non-response state: "always in" (stayers), "ever out" (non-responders), and the total sample over all periods. The data indicates that stayers and non-responders have many significant differences in characteristics and activities. Non-responders are more likely to be younger, to practise in hospitals, in the public sector, and are more likely have lower number of visits and daily expenditure but higher expenditure per visit. This pattern implies that they are concentrated in the lower end of the distribution of activities. A possible explanation for the result that the non-responders are younger than stayers is that young dentists are more likely to shift between dental care institutions, such as between hospitals and clinics, between the public and private sectors, between group- and solo-practice, or between insurance and non-insurance markets. As a result, we lose their information when they swap.

Table 2: Means of dentists' characteristics and activities by patterns of non-response[1]

	Stayers	Non-responders [4]	Total Sample [4]
Dentists' characteristics			
Average patients' age	34.19 (0.16)	33.74 (0.23)	34.00 (0.16)
Dentist population ratio [2]	4.54 (0.06)	4.64 (0.04)	4.58 (0.03)
Dentists' age	41.99(0.18)	37.47 (0.20)**	40.19 (0.14)**
Dentists' activities			
Daily number of visits (NT$)	13.23(0.17)	8.02 (0.10)**	11.02 (0.11)**
Daily expenditure (NT$)	12685.65 (157.89)	8498.25(110.08)**	10909.31 (103.08)**
Expenditure per visit (NT$)	975.65 (4.88)	1058.4 (15.47)**	1010.76 (10.39)*
Amalgam fillings [3]	64.24 (1.42)	35.10 (0.70)**	51.73 (0.74)**
Composite resin fillings [3]	84.62 (1.64)	63.98 (1.15)**	75.76 (0.99)**
Scaling [3]	51.60 (0.71)	34.85 (0.48)**	44.41 (0.44)**
Root canal treatment [3]	21.04 (0.40)	11.94(0.19)**	17.13 (0.21)**
Extractions [3]	24.63 (0.46)	14.16(0.22)**	20.14 (0.24)**
Cleaning [3]	31.59 (0.59)	18.07 (0.29)**	25.79 (0.31)**
Sample size	1527	2921	4448

Note: 1: Standard errors in parentheses.
2: Unit: number of dentists per 10,000 of the population.
3: Unit: numbers per month.
4: Test for significantly different from 'stayers'.
**P value < 0.0001, *P value < 0.01

These findings support the assumption that the selection process in this panel may be associated with endogenous observed variables, i.e. activity-related non-response. It is thus worth paying attention to the framework of selection on observables when testing and correcting the non-response problem.

5. MODELS AND ESTIMATION METHODS

5.1 Two-way fixed effects models for dentists' activity

Model 1: The basic panel data specification

Before considering the problem of non-response we define the models for dentist's activity (y_{it}). We consider two-way fixed effects panel data models of dentist activity, motivated by the two-stage budgeting model. The time effects capture two effects: (1) the change of total activity after global budgeting (2) the change in the mix of services provided after global budgeting. The model is illustrated below:

$$y_{it} = \sum_{j=1}^{18} \alpha_j d_{tj} + \alpha_{19} + \sum_{s=20}^{48} \alpha_s d_{ts} + x_{it}\beta + w_i\gamma + \delta_i + \varepsilon_{it} \qquad (1)$$

The unknown parameters we wish to estimate are $\alpha_1 \sim \alpha_{48}$ (time trends),β, γ, and δ_i (time-invariant individual-specific effects). The model can be estimated using all available observations in the unbalanced panel. The two-way fixed effects model (1) is estimated using the *least squares dummy variable* (LSDV) estimator. This is implemented by including dummy variables for each wave (month effects) and using the 'areg' command in Stata to incorporate dummies for each dentist (individual effects). The estimator permits the use of weighting, that allows us to apply the IPW estimator, and robust standard errors that allow for clustering of dentists within institutions.

Model 2: *A constant policy effect*

Model 2 is a simplified model, with a homogeneous policy effect. To isolate the policy effect of the introduction of global budgeting we first specify a simplified model in which the policy effect is assumed to be constant across all types of dentist. The model replaces the time effects with a linear trend and captures the policy effect with a dummy variable that equals one in all months following the introduction of global budgets. Otherwise the specification is the same as model 1 and it is estimated by LSDV, implemented by the *areg* procedure. It is important to emphasise that model 2 is a special case of model 1. A more general model could allow interactions between the policy dummy and the other regressors, but this is encompassed in our more general specification – model 3 – described below. The purpose of model 2 is to allow ease of interpretation. However the assumption of a once-and-for-all policy effect that is homogeneous across dentists seems rather restrictive and is relaxed in model 3.

Model 3: Heterogeneous policy effects

Model 3 is a more general specification than model 1 in which the parameters of the model, including the individual effects, are allowed to differ pre-and post-global budgeting. This allows us to estimate a separate policy effect for each dentist, by splitting the sample into pre- and post-policy periods and estimating individual effects for both periods. The disadvantage of this model is that it can only be applied to dentists who are in the sample before and after the policy change and the sample is restricted accordingly. The advantage is that the difference in the individual effects gives us individual specific policy responses.

The individual effects (hereafter *"dentist effects"*) are an important component of model 2 and allow us to investigate dentists' responses to the introduction of global budgeting in more detail. The magnitude of the dentist effects measures individual heterogeneity in activities that could not be captured by observable factors in the regression. Because of the length of the panel, this allows us to estimate individual-specific responses to the payment reform as well as calculating the policy effects. The empirical models for the estimation of individual effects and policy effects are based on:

$$\text{Pre-global budget: } y_{it}^{0} = \alpha_1 + \sum_{j=2}^{18} \alpha_j^0 d_{jt} + x_{it}\beta^0 + \delta_i^0 + \varepsilon_{it}^0 \quad \text{t=1\textasciitilde 18} \qquad (2)$$

$$\text{Post-global budget: } y_{it}^{1} = \alpha_{19} + \sum_{j=20}^{48} \alpha_j^1 d_{jt} + x_{it}\beta^1 + \delta_i^1 + \varepsilon_{it}^1 \quad \text{t=19\textasciitilde 48} \qquad (3)$$

where the superscripts 0 and 1 denote pre- and post-global budget respectively. α_1 and α_{19} are constant terms and the reference values for the coefficients of time dummies. The $\alpha^0{}_2$ to $\alpha^0{}_{18}$ are time fixed effects for pre-global budget and $\alpha^1{}_{20}$ to $\alpha^1{}_{48}$ are for post- global budget. They are constant for each dentist.

We use the 'areg' command in Stata to predict the individual fixed effects before and after global budgets. Both are constant over time and are measured relative to the constant terms and time effects. Therefore, the full individual fixed effects are equal to the mean of time fixed effects plus individual fixed effects:

$$a_i^0 = \frac{1}{18}\left[\alpha_1 + \sum_{j=2}^{18} \alpha_j^0\right] + \delta_i^0 \qquad (4)$$

$$a_i^1 = \frac{1}{30}\left[\alpha_{19} + \sum_{j=20}^{48} \alpha_j^1\right] + \delta_i^1 \qquad (5)$$

where $a^0{}_i$ and $a^1{}_i$ represent "full individual dentist effects" pre- and post-global budget respectively. Precisely, they mean the extent of activity at each individual dentist before and after global budgeting respectively. They thus are different for each dentist. The magnitude of the changes of individual fixed effects in response to the introduction of global budgeting is:

$$\Delta_i = a_i^1 - a_i^0 \tag{6}$$

This can be interpreted as, holding other observable variables constant, the extent to which each individual dentist's activity has changed after the introduction of global budgeting, hereafter called the *"policy effect"*. A positive value of policy effect indicates an increase in individual dentists' activity after the introduction of global budgeting and *vice versa*.

5.2 A descriptive model of non-response

So far, the models described in section 5.1 do not take explicit account of unit non-response. To provide evidence on the relevance of non-response for estimation of the models we follow a series of steps: estimating a descriptive model of the factors associated with non-response; comparing the two-way fixed estimates for the balanced sample, the unbalanced sample and the sample of non-responders; computing variable addition tests; estimating the models using inverse probability weights and comparing the weighted and unweighted estimates.

The aim of the descriptive model of non-response model is to examine the determinants of non-response as well as the existence of activity-related non-response. This is done by estimate a pooled probit model for non-response using the full sample of individuals.

In the empirical model, we estimate the probit model for overall non-response[15]. The binary dependent variable equals 1 if the individual has ever been out (non-response) and 0 otherwise. The identification of the factors associated with non-response (z) is somewhat different from previous work, because this panel dataset is different from general survey panel data. Generally, in a survey panel individuals are selected in the initial wave of the survey then they are followed up for several waves, whereas individuals in this panel dataset are identified at

[15] We also estimated separate probit models for each period from the initial period to the last period; the results are similar with the model of overall attrition. Thus for brevity we present the results of overall attrition only.

the 24th period instead of the first period. The values of the variables observed at the first period, as suggested by the literature (Verbeek and Nijman, 1992; Moffitt *et al.*, 1999; Wooldridge, 2002b), are no longer appropriate to predict the non-response propensities in this study. Therefore we apply transformations of the variables.

Building on the work of Fitzgerald *et al.* (1998), Moffit *et al.* (1999) and Diggle and Kenward (1994), the explanatory variables, z_i, for the model of non-response include (1) individual-specific means of dentists' activities and characteristics across all periods, i.e. $\bar{y}_i = \frac{\sum_{t=1}^{T_i} y_{it}}{T_i}$ and $\bar{x}_i = \frac{\sum_{t=1}^{T_i} x_{it}}{T_i}$ $1 \le T_i \le 48$; (2) individual-specific variances of dentists' activities across all periods, i.e. variances of y_{it} from $\bar{y}_i$, $Var(y_i)$; (3) time-invariant individual dentists' characteristics, such as gender, whether practising in deprived areas, ownership (private or public), and types of practice (clinic or hospital), and branch. A general reason for losing observations is miscoding of dentists' individual identification number, which might be associated with the administrative efficiency of the branch. Therefore, the variable for branch membership will be considered as a predictor of the non-response probability.

5.3 Variable addition tests

Verbeek and Nijman (1992) propose a simple variable addition test to examine the influence of non-response. Its rationale is that the selection function of S_{it} itself should not enter the structural model under the null hypothesis of no selection bias. So selection should not be significant in the structural equation at time t[16]. Three possible variables can be included in the regression model. First, the number of waves in which the individual is observed, $T_i = \sum_{s=1}^{T} s_{is}$; second, an indicator for whether the individual is observed in all waves, $c_i = \prod_{s=1}^{T} s_{is}$. Third, an indicator for whether the individual is observed in the subsequent wave, S_{it+1}. Each of these could be added to structural models and estimated with the unbalanced sample. This gives three separate tests for non-response bias. However, the first two additional variables are time-constant for each dentist, and they do not work in the context of the fixed effects panel data model in this paper. Consequently, in this empirical analysis we apply the third variant.

[16] The selection could generate biased estimation in fixed effects contexts only when selection is related to the random error term, ε_{it} (Wooldridge, 2002b). Therefore this test only tests this assumption.

5.4 Inverse probability weighting

To implement the inverse probability weighted (IPW) estimators we estimate separate probit equations for response (S_{it}=1) versus non-response (S_{it}=0) at each wave, $t=1,\ldots,48$, conditional on a set of dentists' characteristics (z_i), as described in section 5.2. The probits for response/non-response are estimated at each month of the panel, in total 48 months, using the full unbalanced panel. The inverse of the predicted selection probability, $1/\hat{p}_{it}$, is then used to weight observations in the least squares estimation of the two-way fixed effects panel data models. We thus obtain weighted least squares (WLS) estimators by minimizing the weighted sum of squared residuals, where each squared residual is weighted by ($1/\hat{p}_{it}$), under the assumption:

$$\Pr\left(s_{it}=1|y_{it},x_{it},z_i\right)=\Pr\left(s_{it}=1|z_i\right) \qquad t=1,\ldots\ldots,48 \tag{6}$$

It is interesting to note that this application is somewhat different from previous applications, such as Wooldridge (2002b) and Contoyannis, Jones, and Rice (2004). First, we use the transformed variables that reflect mean values and variances over all available periods in this analysis, unlike the other applications, where z_i is the value observed at the first or previous wave. Second, we do not restrict the sample to monotone non-response, thus the selection probability at the current wave does not condition solely on the individuals observed at the previous wave. Therefore, we can use the inverse predicted selection probabilities ($1/\hat{p}_{it}$) directly to weight the equations. Under the ignorability assumption (6), the IPW estimator is $\sqrt{n}$ -consistent and asymptotically normal (see e.g., Wooldridge, 2002a). Paradoxically, using the estimated $\hat{p}_{it}$ rather than the true p_{it} and ignoring the implied adjustment to the estimated standard errors leads to more efficient estimates and hence "conservative inference" so that the standard errors are larger than they would be with an adjustment for the use of fitted rather than true probabilities (see also Robins *et al.,* 1995, Wooldridge, 2002a)[17].

[17] When dealing with sample attrition the "IPW-1" estimator presented here can be adapted to allow the elements of z to be up-dated and change over time, for example adding z variables measured at t-1 to predict response at t. This gives the "IPW-2" estimator. In this case the probit model for response at wave t is estimated using only the sample that is observed at t-1: this relies on attrition being an absorbing state and is therefore confined to "monotone attrition", where respondents do not re-enter the panel. Because estimation at each wave is based on a selected sample the predicted probability weights are computed cumulatively. In this version of the estimator the ignorability

The use of the means and variances of the y variables in the model of non-response has some important advantages. First, we do not lose information on dentists who are not observed at the initial period, but are observed at other periods. This means that the models of non-response can be estimated using the full sample of individuals. Second, the transformations capture not only the static effects of determinants on the non-response probit but also the dynamic effects (see e.g, Moffit *et al.,* 1999). The mean values of these variables measure the static effects, while the variances measure the effects of fluctuation on the non-response probability. These transformations are more comprehensive than using the values of the variables in the first wave only, making the ignorability condition on which the IPW estimator relies more plausible. The means and variances of y satisfy the requirement that the z's should be associated with y conditional on x, i.e. that the z's are endogenous (see Moffit *et al.,* 1999, p.132).

condition has to be extended to include future values of y and x (see Wooldridge, 2002b, p.589). However the complex pattern of non-response in our data do not conform to monotone attrition and only the IPW-1 estimator is applicable.

6. RESULTS

6.1 Probit model for non-response

Table 3 presents the estimates of the overall non-response probit model[18]. The first column shows the partial effects of explanatory variables on the non-response probability. The results indicate that the non-response probability is significantly affected by observed variables (z_i). Older and clinic-based dentists are significantly less likely to attrite. Dentists whose patients' average age is older are less likely to attrite.

As expected, dentists who have a greater mean number of visits are less likely to attrite, while those who have higher daily expenditure are more likely to attrite. The non-response propensity is positively affected by the variation of some activities. Dentists who have greater variances of daily number of visits and expenditure per visit, monthly numbers of composite resin fillings and scaling are more likely to attrite, whereas those who have less variance of daily expenditure are more likely to attrite.

It is noteworthy that when we gradually add regressors in a series of estimated non-response probit models, the significant relationship between the non-response propensity and means and variances of activities remains. These findings give evidence of the existence of activity-related non-response.

[18] These results from the pooled model are presented to give an overall sense of the factors associated with non-response. 48 separate probit models were estimated in order to compute the inverse probability weights. For brevity the full results are not presented here.

Table 3: Partial effects for "ever-out" probit model (ever-out=1)

	dF/dx		Std. Err.
Mean of activities			
Daily number of visits	-0.0633	***	(0.0115)
Expenditure per visit	-0.0001		(0.00004)
Daily expenditure	0.00005	***	(0.00001)
Amalgam fillings	0.0003		(0.0004)
Composite resin fillings	-0.0006		(0.0004)
Root canal treatment	-0.0044		(0.0024)
Scaling	-0.0009		(0.0008)
Extractions	0.0016		(0.0011)
Cleaning	-0.0018		(0.0019)
Variance of activities			
Daily number of visits	0.0128	***	(0.0031)
Expenditure per visit	0.000001	**	(0.0000002)
Daily expenditure	-0.00000001	***	(0.000000003)
Amalgam fillings	-0.00002		(0.00001)
Composite resin fillings	0.00002	**	(0.00001)
Root canal treatment	0.0001		(0.0002)
Scaling	0.0001	*	(0.0001)
Extractions	-0.0002	*	(0.0001)
Cleaning	0.0001		(0.0001)
Mean of characteristics			
Patient average age	-0.0058	***	(0.0018)
Dentist population ratio	-0.0010		(0.0133)
Dentists' age	-0.0812	***	(0.0127)
Dentists' age square	0.0008	***	(0.0001)
Male dentist	-0.0090		(0.0191)
Deprived area (=1)	0.0060		(0.0365)
Household income	-0.0021		(0.0018)
Clinic dentist (=1)	-0.1325	**	(0.0491)
Private dentist (=1)	0.0141		(0.0636)
Administrative effect			
Taipei branch	0.0475		(0.0629)
North branch	0.0675		(0.0617)
Central branch	-0.0291		(0.0598)
South branch	-0.0343		(0.0621)
Kaoping branch	0.0284		(0.0541)
Number of observations	3789	Prob > chi2	0.0000
chi2(42)	906.67	Psudo R2	0.3642

Note: We omit coefficients of ICD520-ICD529 from the table.
***P<0.0001 **P<0.01 *P<0.05

6.2 Variable addition tests

Table 4 presents the variable addition test using the next wave indicator (s_{it+1}) in two-way fixed effects estimates of model 1 for nine separate dentists' activities. The test shows evidence of non-response for three activities: numbers of visits, daily expenditure, and monthly numbers of composite resin fillings at a 5% significance level. The negative coefficient on daily expenditure corresponds to the fact that the non-response probabilities are positively correlated to dentists' income. Dentists who remain in the sample provide fewer composite resin fillings because of the strict utilisation review for that service under NHI. This implies that high-fee services may be paid for by patients' out-of-pocket payment.

Table 4 Variable additional tests for non-response: model 1

Dentists' activity	Coefficients	Std. Err.	P > |t|
Daily number of visits	-1.24	0.62	0.045
Expenditure per visit (NT$)	-61.43	37.42	0.101
Daily expenditure (NT$)	-1757.34	653.53	0.007
Amalgam fillings	-3.17	5.88	0.590
Composite resin fillings	-26.39	8.09	0.001
Root canal treatment	-0.07	1.67	0.965
Scaling	-6.14	3.34	0.066
Extractions	-1.18	1.95	0.545
Cleaning	0.81	2.38	0.734

Note: Estimates based on two-way fixed effects panel data models

Because the variable addition tests have low power and do not correct the estimates for non-response bias (Verbeek and Nijman 2000)[19], it is worthwhile to compare the estimates from the balanced and unbalanced panels directly.

6.3 Comparison of coefficients across samples

Table 5 reports the selecteded coefficients for model 1 estimated on the balanced sample, theunbalanced sample and the sample of non-responders based on two-way fixed effects models. The standard errors are in parentheses. Because the explanatory variables for whether practising in deprived areas and private dentists are time-invariant within individual dentists, the

[19] Verbeek and Nijman (1992) suggest that the number of waves in which individuals appear, T_i, has fairly good power, while the test based on $S_{i,t-1}$ has only very limited power.

regressions on the balanced panel drop these two variables. Moreover, due to the larger sample size, the estimates on the unbalanced panel show smaller standard errors.

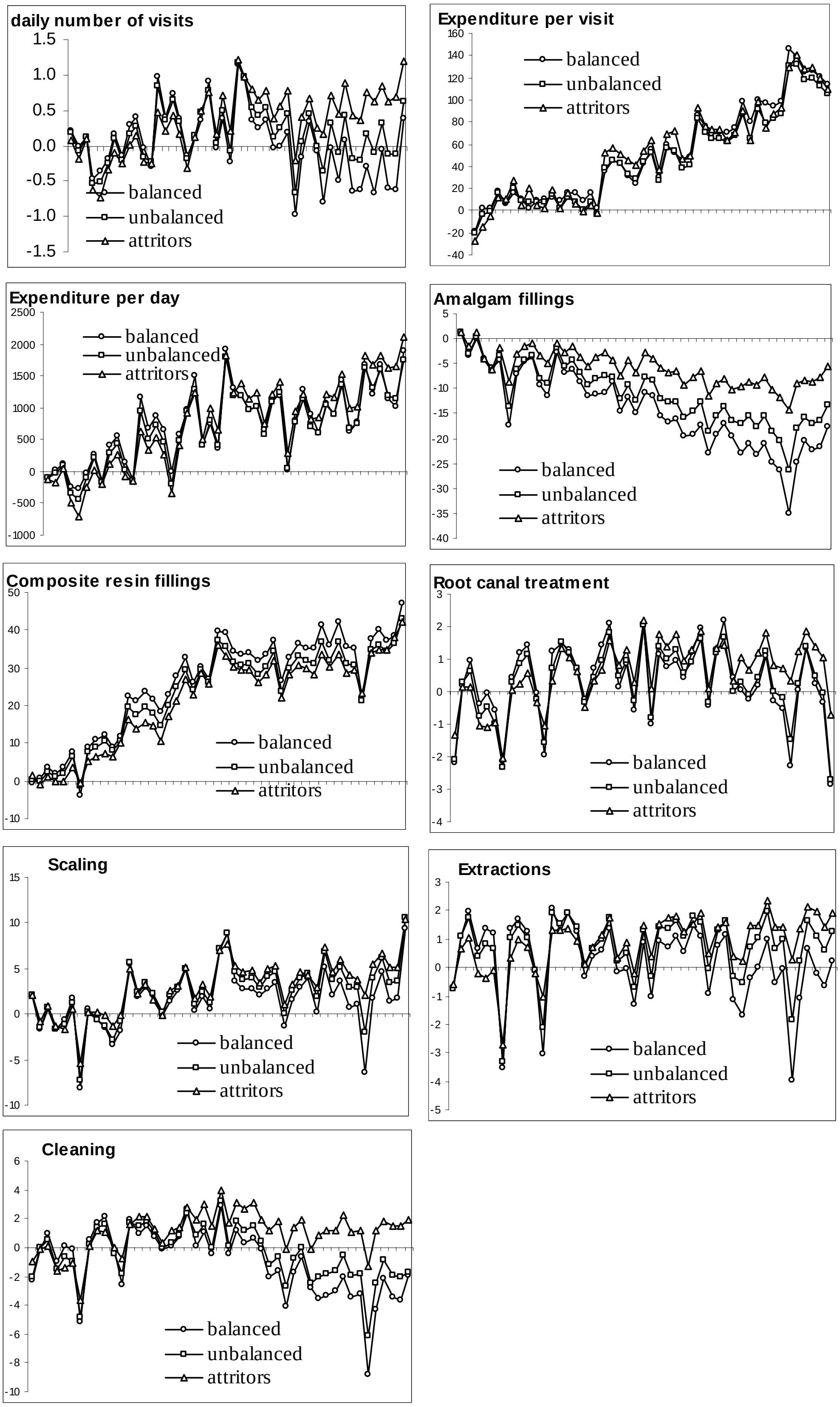
The results show differences in all coefficients, including constant terms, between the balanced and unbalanced samples and between balanced and non-responders samples. In general, the constant terms on the balanced panel are the highest estimates compared to the unbalanced and non-responders samples, with the exception of expenditure per visit. This implies that dentists in the balanced sample might have higher activity than those in the attriting panel because the non-responders tend to supply private services paid by the patient's out-of-pocket payment. This result is consistent with previous analyses and again gives evidence of activity-related non-response.

Figure 1 plots the time effects for model 1 estimated with the three different samples. The conditional time effects reflect average levels of activities across all dentists who are observed in different months. The results show that in some activities there are significantly different trends between the three samples. Generally the average month effects in the balanced sample are lower than those in the sample of non-responders. Since the unbalanced sample is the combination of the balanced and the non-responders samples, the results always stand between the two of them.

Table 5 Two-way fixed effects estimates of selected coefficients for model 1 using different samples (robust standard errors in parentheses)

	Balanced sample NT=75011		Attriting sample NT=55089		Unbalanced sample NT=130100	
Daily number of visits						
Average patient's ages	-0.13	(0.02)	-0.02	(0.01)	-0.05	(0.01)
Dentist population ratio	0.34	(0.16)	-0.67	(0.17)	-0.62	(0.13)
Household income	-0.01	(0.01)	0.004	(0.01)	-0.002	(0.01)
Clinic	-6.50	(0.70)	-0.81	(0.76)	-0.99	(0.75)
Constant	23.35	(1.03)	7.65	(1.48)	11.85	(1.10)
Expenditure per visit (NT$)						
Average patient's ages	1.03	(0.42)	1.40	(0.56)	1.24	(0.43)
Dentist population ratio	-28.73	(14.22)	10.02	(6.47)	3.83	(4.79)
Household income	0.41	(0.36)	-0.71	(0.62)	0.03	(0.37)
Clinic	237.91	(65.39)	-68.10	(28.13)	-66.93	(24.96)
Constant	729.22	(35.47)	1021.09	(116.79)	864.65	(67.36)
Expenditure per day (NT$)						
Average patient's ages	-109.23	(19.0)	-15.06	(8.3)	-38.00	(8.9)
Dentist population ratio	-320.64	(248.3)	-649.10	(177.4)	-660.22	(136.9)
Household income	-8.76	(7.8)	-3.84	(15.1)	-5.13	(8.0)
Clinic	-3716.02	(1104.0)	-663.14	(773.9)	-754.42	(747.9)
Constant	21555.72	(1091.0)	7885.79	(1516.2)	11215.65	(1081.9)
Amalgam fillings						
Average patient's ages	-1.01	(0.11)	-0.10	(0.05)	-0.29	(0.05)
Dentist population ratio	5.40	(2.29)	-3.91	(1.01)	-2.90	(0.79)
Household income	-0.05	(0.09)	0.07	(0.11)	-0.003	(0.07)
Clinic	-47.36	(10.41)	6.27	(3.47)	3.40	(3.17)
Constant	137.90	(9.95)	32.10	(10.74)	62.27	(8.23)
Composite resin fillings						
Average patient's ages	-0.83	(0.15)	-0.09	(0.08)	-0.23	(0.08)
Dentist population ratio	-7.40	(4.11)	-1.40	(1.95)	-2.76	(1.28)
Household income	-0.12	(0.12)	-0.33	(0.17)	-0.20	(0.10)
Clinic	-4.27	(18.44)	0.52	(5.47)	-0.31	(4.89)
Constant	135.97	(14.40)	46.93	(13.87)	57.29	(11.18)
Root canal treatment						
Average patient's ages	0.07	(0.03)	0.04	(0.01)	0.04	(0.01)
Dentist population ratio	0.52	(0.40)	-0.88	(0.27)	-0.93	(0.20)
Household income	-0.005	(0.02)	-0.02	(0.03)	-0.01	(0.02)
Clinic	-0.28	(1.82)	0.38	(1.00)	0.04	(1.07)
Constant	13.25	(2.47)	11.16	(2.52)	13.42	(1.95)
Scaling						
Average patient's ages	-0.37	(0.08)	-0.09	(0.03)	-0.18	(0.03)
Dentist population ratio	1.85	(0.99)	-2.45	(0.68)	-2.31	(0.55)
Household income	0.01	(0.04)	0.06	(0.06)	0.03	(0.04)
Clinic	-41.30	(4.41)	-0.93	(3.19)	-2.35	(3.37)
Constant	93.07	(5.31)	24.18	(6.56)	38.04	(5.17)
Extractions						
Average patient's ages	0.21	(0.05)	0.08	(0.03)	0.10	(0.03)
Dentist population ratio	0.21	(0.47)	-1.50	(0.36)	-1.64	(0.31)
Household income	-0.004	(0.02)	-0.02	(0.03)	-0.003	(0.02)
Clinic	-9.81	(2.14)	-3.33	(1.84)	-3.92	(1.81)
Constant	27.26	(2.81)	16.26	(4.03)	18.99	(2.95)
Cleaning						
Average patient's ages	-0.24	(0.04)	-0.02	(0.02)	-0.08	(0.02)
Dentist population ratio	2.17	(0.84)	-1.56	(0.39)	-1.65	(0.30)
Household income	0.02	(0.03)	-0.01	(0.04)	0.01	(0.02)
Clinic	-9.80	(3.94)	1.73	(1.46)	1.16	(1.50)
Constant	31.58	(3.25)	18.36	(3.88)	23.14	(2.88)

Figure 1: Estimates of time trends in model 1 for different samples



The differences of time effects in the balanced sample and the sample of non-responders become wider incrementally, especially after the introduction of global budgeting. For example, the trends of daily number of visits and cleaning show slight increases among the non-responders, whereas they decrease in the balanced sample. A significant example is amalgam fillings: the balanced sample shows a rapidly decreasing trend, while the non-responders show a steady decline. Conversely, the increasing trend of composite resin fillings in the balanced sample is sharper than that among the non-responders. The results imply that non-response may be associated with the introduction of global budgeting. Meanwhile the introduction of global budgeting itself affects dentists' activities and mix of services.

In summary, considering the dentist activity equations based on two-way fixed effects panel data models, the estimators in the balanced and the unbalanced panel are systematically different, especially in the constant terms and the month dummies. This suggests that the non-response may play a significant role in this panel dataset. However, whether non-response generates biased estimates parameters of interest needs further tests. Therefore, we apply inverse probability weighted (IPW) estimators in the next section.

6.4 Inverse probability weighted (IPW) estimators

Table 6 presents the estimated coefficients on selected explanatory variables for the weighted and the unweighted equations based on two-way fixed effects estimates of model 1 using the unbalanced panel[20]. The results show differences in the coefficients on the constant term and some explanatory variables -deprived areas, clinic, and private - between the weighted and unweighted estimates. This indicates activity-related non-response. The results show that the coefficients on the dentist population ratio are very similar between the two estimators.

---

[20] The sample sizes differ for weighted and unweighted estimates as inverse probability weights could not be computed for some dentists due to lack of information on their age or activities.

Table 6: Weighted and unweighted estimates of coefficients from model 1

	Weighted NT=122616		Unweighted NT=130100		Differences
Daily number of visits					
Dentist population ratio	-0.61	(0.15)	-0.62	(0.13)	0.01
Deprived areas (=1)	-0.66	(1.22)	0.11	(0.84)	-0.77
Clinic dentist (=1)	0.42	(0.99)	-0.99	(0.75)	1.40
Private dentist (=1)	2.83	(1.09)	4.60	(0.77)	-1.77
Constant	17.39	(8.19)	11.85	(1.10)	5.54
Expenditure per visit					
Dentist population ratio	8.92	(6.53)	3.83	(4.79)	5.09
Deprived areas (=1)	-35.32	(35.31)	-44.45	(31.73)	9.13
Clinic dentist (=1)	-61.65	(30.05)	-66.93	(24.96)	5.28
Private dentist (=1)	227.99	(51.15)	144.96	(29.23)	83.04
Constant	1288.13	(245.99)	864.65	(67.36)	423.48
Daily Expenditure					
Dentist population ratio	-647.36	(169.34)	-660.22	(136.85)	12.86
Deprived areas (=1)	-1122.69	(1239.14)	-279.02	(735.05)	-843.67
Clinic dentist (=1)	702.62	(1070.92)	-754.42	(747.93)	1457.04
Private dentist (=1)	2564.09	(1139.18)	4323.69	(690.80)	-1759.60
Constant	18012.57	(9085.80)	11215.65	(1081.87)	6796.92
Amalgam fillings					
Dentist population ratio	-3.37	(0.86)	-2.90	(0.79)	-0.47
Deprived areas (=1)	9.80	(7.53)	9.98	(6.58)	-0.17
Clinic dentist (=1)	8.31	(5.07)	3.40	(3.17)	4.91
Private dentist (=1)	11.76	(5.74)	18.13	(4.87)	-6.37
Constant	74.61	(25.84)	62.27	(8.23)	12.34
Composite Resin Fillings					
Dentist population ratio	-3.69	(1.70)	-2.76	(1.28)	-0.94
Deprived areas (=1)	-13.29	(7.20)	-8.84	(5.61)	-4.45
Clinic dentist (=1)	5.00	(7.08)	-0.31	(4.89)	5.31
Private dentist (=1)	22.37	(7.21)	29.42	(5.97)	-7.05
Constant	59.94	(23.02)	57.29	(11.18)	2.65
Root Canal Treatment					
Dentist population ratio	-0.77	(0.28)	-0.93	(0.20)	0.16
Deprived areas (=1)	-0.52	(1.69)	0.52	(1.42)	-1.04
Clinic dentist (=1)	2.04	(1.50)	0.04	(1.07)	2.00
Private dentist (=1)	3.25	(1.74)	5.77	(1.24)	-2.52
Constant	24.97	(13.21)	13.42	(1.95)	11.55
Scaling					
Dentist population ratio	-2.28	(0.60)	-2.31	(0.55)	0.03
Deprived areas (=1)	-2.30	(5.30)	0.36	(3.54)	-2.66
Clinic dentist (=1)	3.86	(4.34)	-2.35	(3.37)	6.21
Private dentist (=1)	13.04	(4.91)	20.69	(3.58)	-7.65
Constant	64.55	(36.61)	38.04	(5.17)	26.51
Extractions					
Dentist population ratio	-1.35	(0.33)	-1.64	(0.31)	0.29
Deprived areas (=1)	-3.08	(2.73)	-1.01	(2.16)	-2.07
Clinic dentist (=1)	-0.51	(2.28)	-3.92	(1.81)	3.41
Private dentist (=1)	4.78	(2.64)	9.12	(2.06)	-4.34
Constant	37.90	(22.63)	18.99	(2.95)	18.92
Cleaning					
Dentist population ratio	-1.70	(0.39)	-1.65	(0.30)	-0.04
Deprived areas (=1)	0.03	(2.64)	0.36	(2.33)	-0.33
Clinic dentist (=1)	3.82	(2.15)	1.16	(1.50)	2.66
Private dentist (=1)	5.63	(2.66)	8.72	(1.97)	-3.10
Constant	30.38	(12.75)	23.14	(2.88)	7.25

Figure 2 graphs the time trends from the two estimators for model 1. The average month effects in the weighted estimation are lower than these in the unweighted estimation. Although the month effects are different, the patterns over 48 months are similar. Moreover, the graph shows that differences in expenditure per visit are very small. This implies that non-response has little correlation with the intensity of treatment per visit although it might be correlated with the quantity of specific treatments.

Table 7 reports the Hausman statistics and significance levels. The first Hausman test (labelled "all coefficients") is calculated for the null hypothesis that none of the coefficients differ across the two estimators. The second (labelled "all coefficients but constant") allows the constant to differ across the two estimators. We find few significant effects of non-response on these coefficients. The Hausman tests fail to reject equality of the coefficients between the two estimates, especially when allowing the constants to differ, with the exceptions of root canal treatment and extractions. This thus suggests that non-response is not correlated to dentists' aggregate activity, i.e. number of visits, expenditure per visit, or daily expenditure, but may be correlated to specific activities, such as root canal treatment and extractions. It generally implies that the estimates of aggregate activity equations using the balanced and unbalanced panels in the framework of selection on observables are consistent.

Table 7 Hausman test for differences between weighted and unweighted estimates of model 1

	All coefficients [1]		All coefficients but constant [2]	
	Chi squares	P > Chi2	Chi square	P > Chi2
Daily number of visits	471.00	0.0000	45.44	0.8848
Expenditure per visit	54.86	0.7282	80.25	0.0594
Daily expenditure	215.88	0.0000	55.12	0.5954
Amalgam fillings	23.47	1.0000	9.55	1.0000
Composite resin fillings	32.26	0.9995	21.02	1.0000
Root canal treatment	81.45	0.0185	82.88	0.0142
Scaling	54.82	0.5943	29.95	0.9992
Extractions	146.11	0.0000	156.88	0.0000
Cleaning	62.10	0.4014	49.05	0.8427

Notes: 1: Tests for all coefficients across the two models.
2: Tests for coefficients excluding constant terms.
3. We treat the estimators of coefficients in the unweighted model as efficient, due to smaller variances, while those in the weighted model are consistent under non-response.

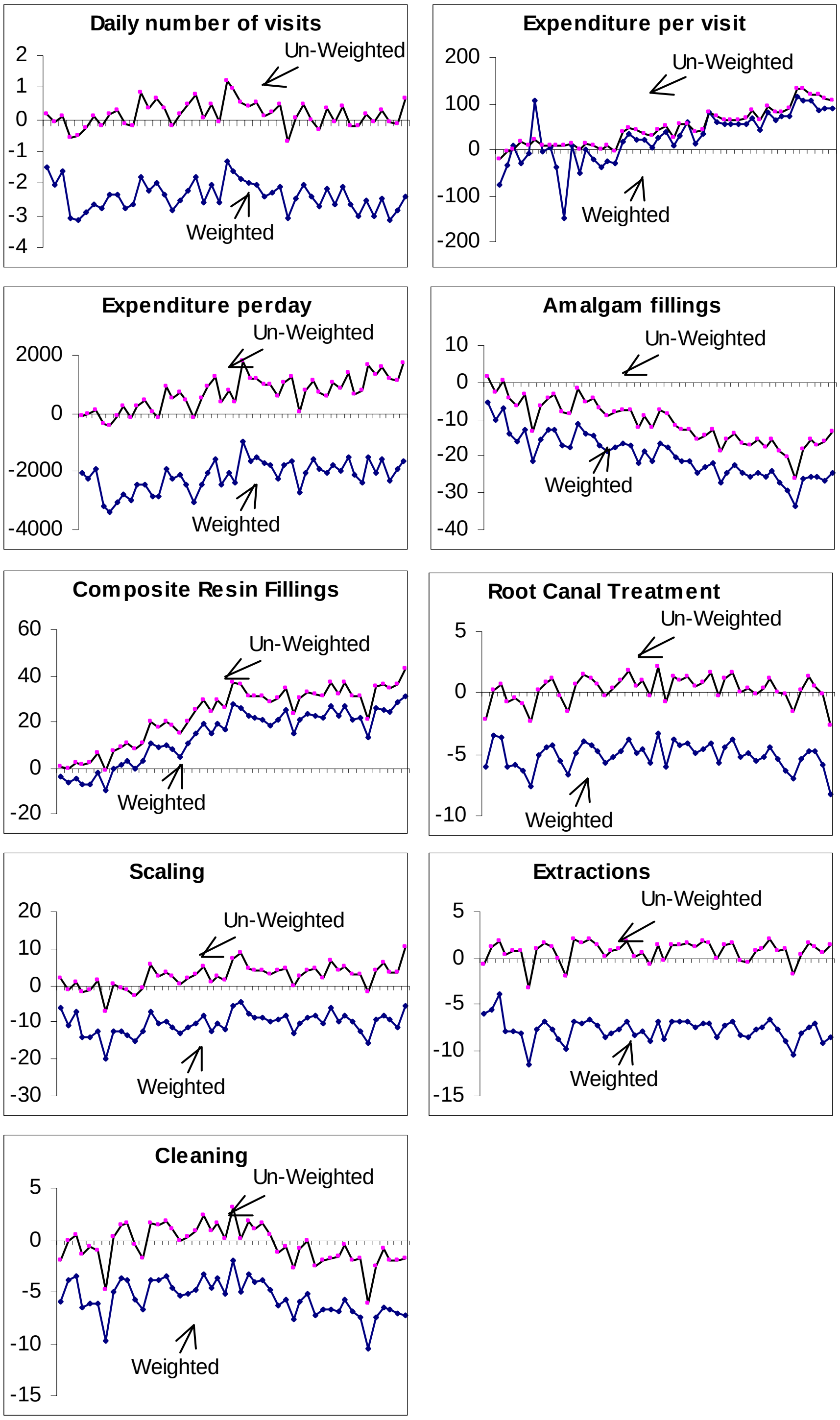
Table 8 presents the weighted and unweighted estimates of model 2: the simplified model that allows for a linear trend and a constant policy effect. The table shows the estimates of the policy effect given by the coefficient and standard error for the dummy variable for global budgeting[21]. The weighted estimates do differ from the unweighted, although many are similar in magnitude. The most striking contrast is for expenditure per visit, where the estimate changes sign, although the estimates are not statistically significant. These findings can be explored further with model 3 that allows for dentist-specific policy effects.

Table 8: Weighted and unweighted estimates of effect of global budgets from model 2

	Weighted		Unweighted	
Daily number of visits	0.32	(0.05)	0.39	(0.05)
Expenditure per visit	-3.01	(2.82)	4.30	(2.87)
Daily Expenditure	248.50	(58.1)	390.84	(54.91)
Amalgam fillings	-1.12	(0.61)	-0.73	(0.55)
Composite Resin Fillings	10.29	(0.88)	11.03	(0.82)
Root Canal Treatment	0.90	(0.15)	1.10	(0.13)
Scaling	1.82	(0.30)	1.99	(0.27)
Extractions	0.03	(0.18)	0.10	(0.15)
Cleaning	1.80	(0.22)	1.98	(0.19)

[21] The coefficients for the other variables in the model are omitted for brevity.

Figure 2: Weighted and unweighted estimates of time trend for model 1



6.5 Allowing for heterogeneous policy effects

To provide further evidence on the influence of non-response bias, considering global budgeting, we compare the estimates of individual fixed effects (dentist effects) pre- and post-global budgeting and the policy effects. These are estimated using the more general specification of model 3, as defined in equations (2)-(6) above. The comparison is focused on the correlation coefficients of the estimates in the weighted and unweighted models. Higher correlation coefficients indicate that the estimates from the two models are close to each other. Table 9 reports the correlation coefficients.

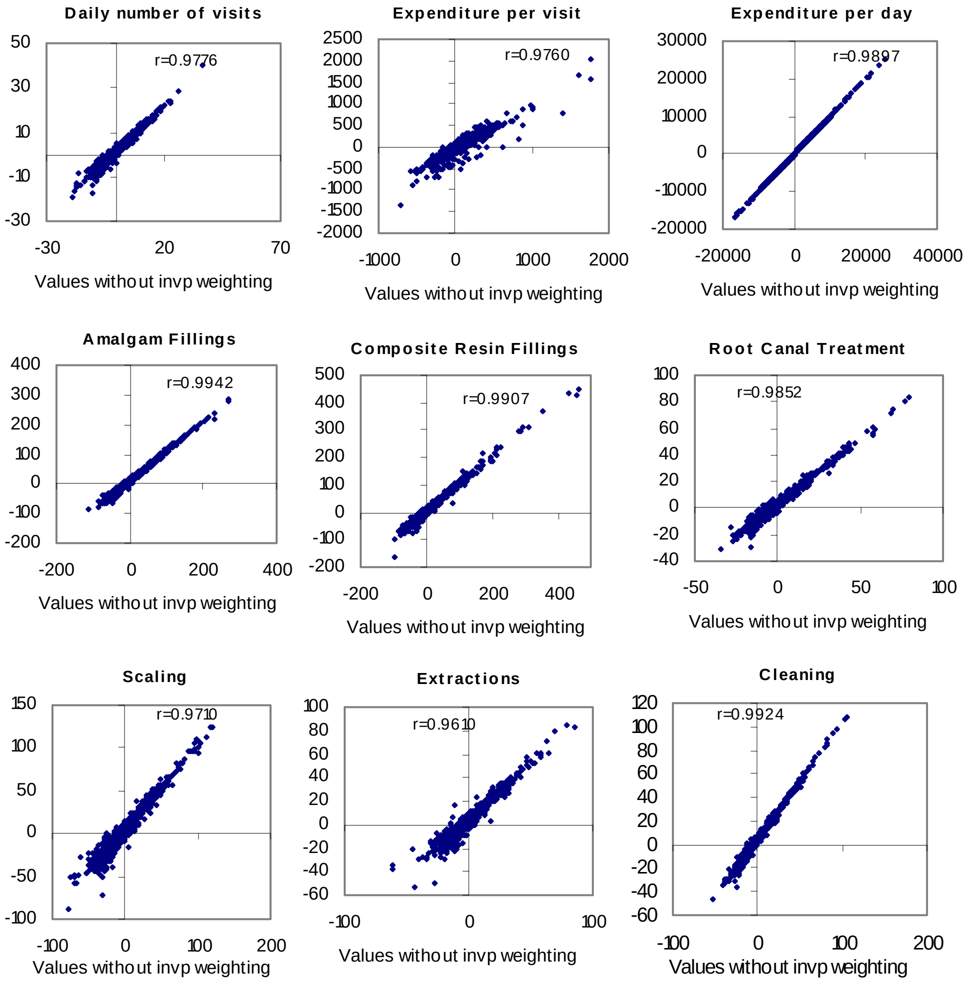
Table 9 Correlation coefficients between the weighted and unweighted estimates of model 3 (ρ)

	Dentist individual effects		Policy effects
	Before global budgeting	After global budgeting	
Daily number of visits	0.9776	0.9963	0.9091
Expenditure per visit	0.9760	0.9980	0.9585
Daily expenditure	0.9897	0.9957	0.9074
Amalgam fillings	0.9942	0.9974	0.9780
Composite resin fillings	0.9907	0.9974	0.9774
Root canal treatment	0.9852	0.9968	0.9430
Scaling	0.9710	0.9959	0.9090
Extractions	0.9610	0.9971	0.8605
Cleaning	0.9924	0.9960	0.9691

Figure 3 and 4 graph the relation of dentist effects in the weighted and unweighted estimates of model 3 pre- and post- global budgeting respectively. The charts show that there are high correlations between the two estimators. The correlation coefficients range from 0.961 to 0.998. Moreover, the correlation post-global budgeting is stronger than pre-global budgeting. This implies that non-response has relatively less influence on dentist effects after the introduction of global budgeting. One explanation is that dentists attrite from the sample after the introduction of global budgeting due to activity-related non-response. Consequently, post-global budgeting dentist effects are consistent between the two regressions. Furthermore, the manifest picture that the two estimates disperse widely at the low end of the distribution of dentist effects indicates that non-response has a larger influence on dentists at the low end of the activity distribution than on dentists at the upper end. This again supports the observation that dentists with fewer activities, but not income, are more likely to be missing from the sample.

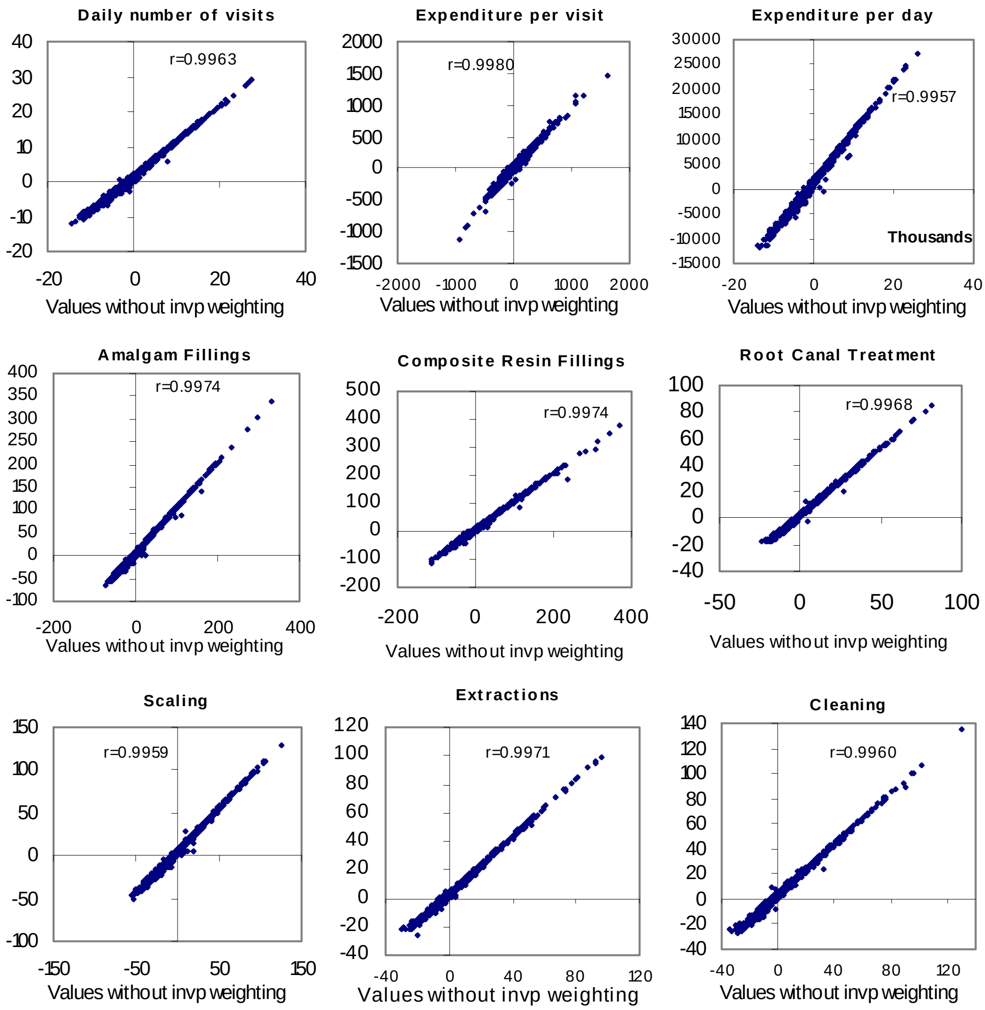
Figure 5 plots the correlation of policy effects between the weighted and unweighted estimates. The correlation coefficients are as high as 0.91, although they are lower than for dentist effects. The distribution of the correlation is more dispersed than that of dentist effects, because of the smaller sample size in the estimation of policy effects. As the policy effect is defined as the change of dentist effects between pre-and post-global budgeting, it only takes into account the dentists who are observed in both periods.

Figure 3 Correlation of dentist effects between weighted and unweighted estimates of model 3, pre-global budgeting



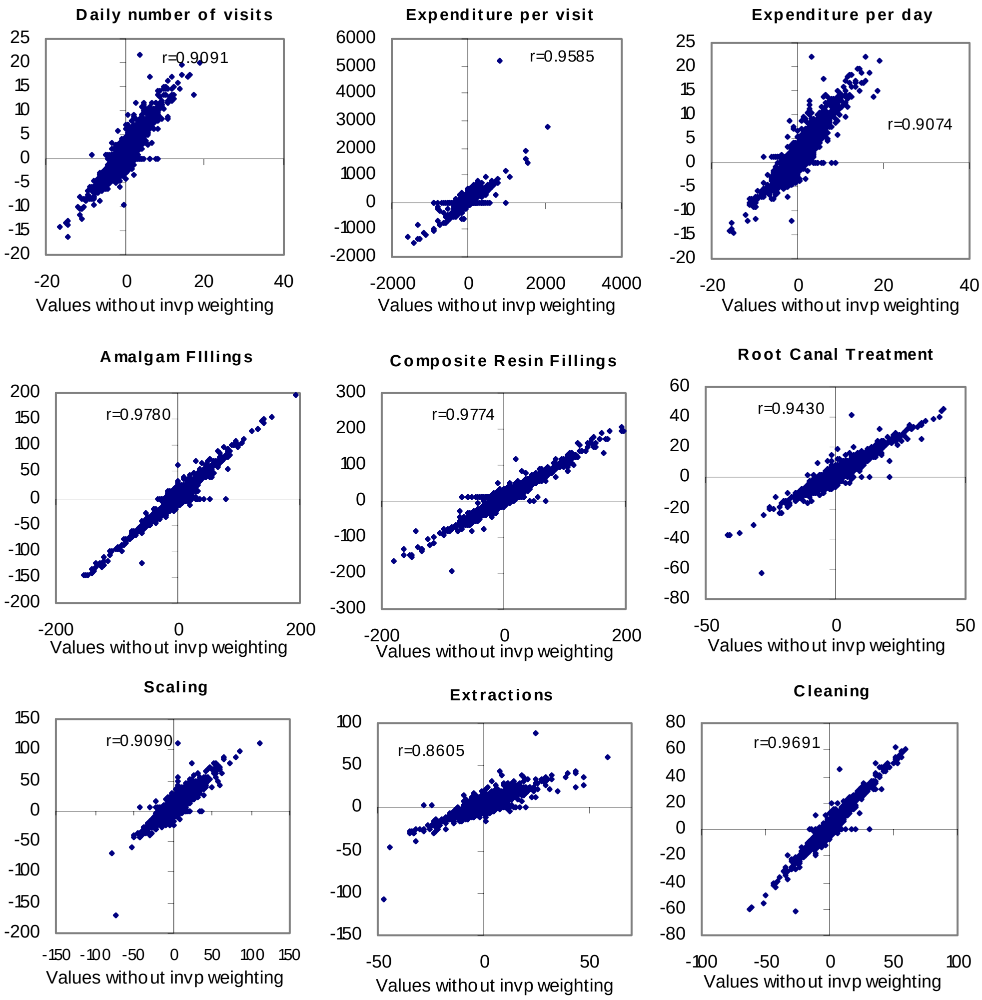
Notes: X-axis: values without invp weighting;
Y-axis: values with invp weighting

Figure 4 Correlation of dentist effects between weighted and unweighted estimates of model 3, post-global budgeting



Notes: X-axis: values without invp weighting;
Y-axis: values with invp weighting

Figure 5 Correlation of policy effects between weighted and unweighted estimates



Notes: X-axis: values without invp weighting;
Y-axis: values with invp weighting

7. CONCLUSIONS AND POLICY IMPLICATIONS

This paper evaluates the impact of the introduction of global budgeting on dentists' activity in Taiwan using a unique and rich panel dataset that was created specifically for the task. The panel data for 4424 dentists over 48 months, January 1997 to December 2000, was drawn from the BNHI's data warehouse. The 66% non-response rate is an important feature of this panel data. This paper has considered the sample selection problem, where selection is generated by observable variables, which are endogenous to dentist activities. We have examined the existence of activity-related non-response by using: variable addition tests and inversion tests. We have shown that consistent estimates of dentist activity equations, correcting for selection on observables, can be obtained from estimates that weight by the inverse selection probability. This paper has suggested an alternative specification for the selection probability function where we apply two transformations of observed variables in the estimation of non-response probit models that include all participants each month rather than considering monotone non-response only.

The analysis yields the following findings:

1. Descriptive analysis shows that the observed characteristics of dentists who always respond and those with missing data are significantly different. Non-responders are more likely to be younger and to practise in hospitals rather than in clinics.
2. The non-response propensity probit analysis finds evidence of activity-related non-response conditioning on a number of other characteristics. Non-responders tend to have a lower number of visits per day and more expenditure per day than the average of the population. Non-responders also tend to have less stable numbers of visits per day. The magnitude of the effects of these variables on the non-response propensity is small, which suggests that the non-response correlated with those variables is unlikely to lead to biased estimates of dentist activity equations.
3. The variable addition tests, using response of the next wave, show evidence of non-response bias: retention at the next wave is negatively associated with daily expenditure and monthly number of composite resin fillings. This suggests that dentists who remain in the sample have lower daily expenditure and composite resin fillings.

4. A comparison of estimates from the balanced and unbalanced panels shows some substantive differences in time effects and intercept terms rather than in the slope coefficients of key regressors.
5. The inverse probability weighted estimators for dentist activity present similar results in sign and magnitude of the variables of interest. However, non-response appears to affect the time effects and intercepts.
6. The impact of non-response on policy effects is more apparent than on individual dentist effects.

To sum up, there is evidence of activity-related non-response. One explanation of the result that stayers have lower levels of income may be the budget control due to the introduction of global budgeting. Because dentists are put directly at risk due to the cost of their supply behaviour under global budgeting, dentists may suggest private services to patients. The results may also demonstrate that dentists attempt to constrain the amount of activity from the NHI's benefit package, and shift the services to be paid for by patients' out-of-pocket payments. In the long run, this would lead to two-tier dental care, where patients receive less quantity and low charge dental care from the NHI's benefit package, but receive more quantity and high charge services paid for by the out-of-pocket payment. A two-tier system would lead to deterioration in the equity of health care provision. This result is thus further evidence of the existence of a potential two-tier dental care system.

REFERENCES

Becketti, S. et al. (1988). The panel study of income dynamics after fourteen years: an evaluation. *Journal of Labor Economics* 6(4), 472-492.

Benstetter, F and A. Wambach (2001). Strategic interaction in the market for physician services: the treadmill effect in a fixed budget system. *CESifo working paper* NO: 427, German.

Contoyannis, P., A.M. Jones and N. Rice (2004). The dynamics of health in the British household panel survey. *Journal of Applied Econometrics* 19, 473-503.

Diggle, P. and M.G.Kenward (1994). Informative drop-out in longitudinal data analysis. *Applied Statistics* 43(1), 49-93.

Fitzgerald, J., P. Gottschalk and R. Moffitt (1998). An analysis of sample attrition in panel data: the Michigan Panel Study of Income Dynamics. *The Journal of Human Resources* 33(2), 251-299.

Fitzmaurice, G.M., A.F. Heath and P. Clifford (1996). Logistic regression models for binary panel data with attrition. *Journal of the Royal Statistical Society, Series A (Statistics in Society)* 159(2), 249-263.

Hausman, A. and D.A. Wise (1979). Attrition bias in experimental and panel data: the Gary Income Maintenance Experiment. *Econometrica* 47(2), 455-473.

Heckman, J.J. (1976). The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models. *The Annals of Economic and Social Measurement* 5, 475-492.

Heckman, J.J. (1979). Sample selection bias as a specification error. *Econometrica* 47(1), 153-162.

Heckman, J.J. (1997). Instrumental variables: a study of implicit behavioral assumptions used in making program evaluations. *The Journal of Human Resources* 32(3), 441-461.

Heckman, J.J. (2000). Causal parameters and policy analysis in economics: a twentieth century retrospective. *The Quarterly Journal of Economics* February, 45-97.

Heckman, J.J. (2001). Micro data, heterogeneity, and the evaluation of public policy: Nobel lecture. *Journal of Political Economy* 109(4), 673-748.

Little, R.J.A. and D.B. Rubin (1987). *Statistical Analysis with Missing Data.* New York:: Wiley.

Lee, M-C and A. Jones (2004). How did dentists respond to the introduction of global budgets in Taiwan? An evaluation using individual panel data. *International Journal of Health Care Finance and Economics* 4, 307-326.

Manning, WG et al (1987). Health insurance and the demand for medical care. *American Economic Review* 77(3), 251-277.

Manski, C.F. (1989). Anatomy of the selection problem. *Journal of Human Resources* 24(3), 343-360.

Manski, C.F. (1995). *Identification Problems in the Social Sciences.* Cambridge: Harvard University Press.

Moffitt, R., J. Fitzgerald and P. Gottschalk (1999). Sample attrition in panel data: the role of selection on observables. *Annales D'Economie et de Statistique* 55-56, 129-152.

Molenberghs, G., M.G. Kenward and E. Lesaffre (1997). The analysis of longitudinal ordinal data with non-random drop-out. *Biometrika* 84(1), 33-44.

Nijman, T. and M. Verbeek (1992). Nonresponse in panel data: the impact of estimates of a life cycle consumption function. *Journal of Applied Econometrics* 7(3), 243-257.

Robins, J.M., A. Rotnitsky and L.P. Zhao (1995). Estimation of regression coefficients when some regressors are not always observed. *Journal of the American Statistical Association* 89(427), 846-866.

Rochaix, L (1993). Financial incentives for physicians: the Quebec experience. *Health Economics* 2(1), 163-176.

Rotnitzky, A. and J. Robins, (1994) Analysis of semi-parametric regression models with non-ignorable non-response. *Statistics in Medicine* 16, 81-102.

Sintonen, H. and I. Linnosmaa. (2000). Economics of Dental Services. In: A. J. Culyer and J. P. Newhouse (Eds). *Handbook of Health Economics*, Amsterdam: Elsevier.

Vella, F. (1998). Estimating models with sample selection bias: a survey. *The Journal of Human Resources* 33(1), 127-169.

Vella, F. and M. Verbeek (1999). Estimating and interpreting models with endogenous treatment effects. *Journal of Business & Economic Statistics* 17(4), 473-478.

Vella, F. and M. Verbeek (1999). Two-step estimation of panel data models with censored endogenous variables and selection bias. *Journal of Econometrics* 90, 239-263.

Verbeek, M. and T. Nijman (1992). Testing for selectivity bias in panel data Models. *International Economic Review* 33(3), 681-703.

Verbeek, M. and T. Nijman (1995). Incomplete panel and selection bias. In L Matyas and P. Sevestre (Eds). *The Econometrics of Panel Data: An Handbook of the Theory with Application*. Klumer Academic Publishers.

Wooldridge, J.M. (1995). Selection corrections for panel data models under conditional mean independence assumptions. *Journal of Econometrics* 68, 115-132.

Wooldridge, J.M. (2002a). Inverse probability weighted M-estimation for sample selection, attrition, and stratification. *Portuguese Economic Journal* 1, 117-139.

Wooldridge, J.M. (2002b). *Econometric Analysis of Cross Section and Panel Data.* Cambridge, MA: MIT Press.

Wooldridge, J.M. (2004). Inverse probability weighted estimation for general missing data problems. *CeMMAP working papers, CWP05/04*. Centre for Microdata Methods and Practice, Institute for Fiscal Studies, U.K.