Response bias in job satisfaction surveys: English general practitioners

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Abstract
Job satisfaction affects propensity to quit, actual quits, and job performance. Hence it is of interest to survey workers to investigate their satisfaction and the factors affecting satisfaction. But survey respondents may be untypical of the workforce in unobservable respects which are correlated with satisfaction. In particular satisfaction may affect the propensity to respond to job satisfaction surveys, so that estimates of average satisfaction and the effects of determinants of satisfaction may be biased.

We examine response bias using data from a postal job satisfaction survey of family doctors. We link all the sampled doctors to an administrative database and so have information on the characteristics of responders and non-responders. Thus we can control for both selection on observables and on unobservables. Allowing for selection increases the estimate of mean job satisfaction in 2005 by between 0.4 to 1.0 from uncorrected sample mean of 5.27 (on a 1 to 7 scale). Correction for response bias also increase the estimated change in mean job satisfaction between 2004 and 2005 from 0.60 to 1.03. Estimates of the determinants of job satisfaction are insensitive to response bias.

JEL Nos: J28, J44, I18

Keywords: Job satisfaction. Response bias. Sample selection. Family practitioners.

Acknowledgements
NPCRDC receives core funding from the Department of Health. The views expressed are those of the authors and not necessarily those of the funders. We are grateful for comments at seminars in Aberdeen and York.

1 Introduction

Lower job satisfaction has been shown to increase the proportion of the workforce intending to quit (Shields and Ward, 2001), to increase actual quits, to lower participation rates (Clark, 2001; Clark et al., 1999; Laband and Lentz, 1998; Akerlof et al., 1988), and to increase absenteeism (Clegg, 1983). It has also been found to be associated with worse performance on the job (DeVoe et al, 2002; Grol et al 1985).

Job satisfaction data provide information on the non-pecuniary aspects of jobs which is particularly relevant in many public sector labour markets where wages are nationally negotiated and cannot be altered by local public employers. Local public sector employers will however be able to alter non-pecuniary aspects of jobs to attract and retain staff. In public sector jobs intrinsic and public service motivation may be more important than in the private sector, which also shifts the focus away from pay to non-pecuniary factors. Lower job satisfaction reduces the supply of labour at any given wage or, equivalently, raises the cost of maintaining a workforce of given size. It is necessary to understand the relationships between job characteristics, including those amenable to policy, personal characteristics, job satisfaction and intentions to quit in order to choose the most cost-effective policies to reduce turnover.

Thus both the average level of satisfaction in the workforce and the effects of policy instruments on satisfaction are of interest to large public sector employers such as the NHS. However the average satisfaction of respondents reported in surveys of job satisfaction may not be a good estimate of the average satisfaction of the workforce as a whole: respondents may differ in observable and in unobservable characteristics from the population. Differences only in observable characteristics are relatively easy to deal if these characteristics are observed for the whole workforce. Estimating mean satisfaction conditional on the observed characteristics and then applying the estimated coefficients to population mean characteristics will produce unbiased estimates of mean population satisfaction. Moreover the estimated coefficients will provide unbiased estimates of the effects of the characteristics on satisfaction.

But propensity to respond to job satisfaction surveys may be affected by job satisfaction. Less satisfied workers may be more likely to respond to surveys regarding their job in order to 'vent their frustration', while their more satisfied colleagues may be less likely to respond if they feel no need to change their current situation. Conversely, less satisfied workers may be less motivated to carry out any extra work-related tasks and may therefore be less likely to respond.

Job satisfaction is more likely to affect response when surveys cover a specific set of workers and are clearly intended to focus on job satisfaction. Figure 1 plots the response rates and mean respondent job satisfaction for 11 job satisfaction surveys for NHS doctors, 5 for English GPs, 4 for Scottish GPs and 2 for Scottish consultants. There is a strong negative association (R^2 = 0.71 for the 9 GP surveys; R^2 = 0.59 for all surveys). Surveys with lower response rates tend to have higher mean satisfaction. This suggests that less satisfied doctors are more likely to respond to job satisfaction surveys and raises the a number of questions. Does such response bias lead to the mean of respondents always being less than the true population mean? How reliable are estimates of changes in mean satisfaction over time: if mean reported satisfaction has increased but response rates fallen is it possible that the population mean satisfaction has in fact decreased? Are the estimated effects of doctor characteristics on job satisfaction reliable if no attempt is made to allow for response bias.

We attempt to answer these questions first by setting out in section 2 the potential problems raised by response bias and considering the circumstances in which response bias induces the negative correlation between mean reported satisfaction and response rates shown in Figure 1. We show that even if response depends only on satisfaction and is not affected by other observable or unobservable factors, the resulting response bias may lead to either over or under estimates of population job satisfaction. In the absence of any clear theoretical answers, we attempt to use the data from one of the surveys in Figure 1 examine the implications of response bias. Section 3 describes the data from the 2005 survey of English GPs, and section 4 sets out the methods used to mitigate the effects of response bias. Section 5 presents the results, showing the magnitude of the biases in estimating population satisfaction by the mean satisfaction of the sample respondents and in estimating the determinants of job satisfaction. Section 6 concludes.

2 Effects of response bias

The latent propensity r_i^* to respond to a job satisfaction questionnaire depends on exogenous factors **x**, and satisfaction s_i^*

$$r_i^* = \mathbf{x}_i'\boldsymbol{\beta}_1 + \gamma s_i^* + \varepsilon_i \tag{1}$$

where satisfaction is determined by

$$s_i^* = \mathbf{x}_i'\boldsymbol{\beta}_2 + u_i \tag{2}$$

ε and u are jointly normal. ε has zero mean conditional on the elements in **x** which have a non-zero coefficient in $\boldsymbol{\beta}_2$ and u has zero mean conditional respectively on the elements in **x** which have a non-zero coefficient in $\boldsymbol{\beta}_1$. .

Suppose for the moment that respondents report satisfaction as a continuous cardinal variable. We observe s_i^* if and only if

$$r_i^* = \mathbf{x}_i'\boldsymbol{\beta}_1 + \gamma\mathbf{x}_i'\boldsymbol{\beta}_2 + \gamma u_i + \varepsilon_i = \mathbf{x}_i'\boldsymbol{\beta} + v_i > 0 \tag{3}$$

where $\boldsymbol{\beta} = \boldsymbol{\beta}_1 + \gamma\boldsymbol{\beta}_2$ and $v_i = \gamma u_i + \varepsilon_i$. The elements in the coefficient vector $\boldsymbol{\beta}$ are β_{1j}, $\gamma\beta_{2j}$, or $\beta_{1j} + \gamma\beta_{2j}$, depending on whether the j'th variable is has a direct effect only on response propensity, only on satisfaction, or on both.

The expected value of reported satisfaction is

$$\begin{aligned} E\left[s_i^* \middle| \mathbf{x}_i, r_i^* > 0\right] &= \mathbf{x}_{2i}'\boldsymbol{\beta}_2 + E\left[u_i \middle| r_i^* > 0\right] = \mathbf{x}_{2i}'\boldsymbol{\beta}_2 + E\left[u_i \middle| v_i \ge -\mathbf{x}_i'\boldsymbol{\beta}\right] \\ &= \mathbf{x}_{2i}'\boldsymbol{\beta}_2 + K(\mathbf{x}_i'\boldsymbol{\beta}) \end{aligned} \tag{4}$$

Only if the mean of u_i conditional on v_i is identically zero will the selection term $K(\mathbf{x}_i'\boldsymbol{\beta})$ be zero. Since u, ε have a joint normal distribution $v = \gamma u + \varepsilon$ is a normal variate, and the mean of u conditional on v is linear in v:

$$u_i = b_{uv} v_i + \omega_i = \frac{\sigma_{uv}}{\sigma_v^2} v_i + \omega_i, \quad \mathrm{E}\left[\omega_i \middle| v_i\right] = 0, \tag{5}$$

where $\sigma_{uv} = \gamma\sigma_u^2 + \sigma_{u\varepsilon}$ is the covariance of u and v and $\sigma_v^2 = \gamma^2\sigma_u^2 + \sigma_\varepsilon^2 + 2\gamma\sigma_{u\varepsilon}$ is the variance of v. The selection term in (4) is

$$K(\mathbf{x}_i'\boldsymbol{\beta}) = b_{uv} E\left[v_i \middle| v_i \geq -\mathbf{x}_i'\boldsymbol{\beta}\right] = b_{uv}\sigma_v \lambda(\mathbf{x}_i'\boldsymbol{\beta}/\sigma_v) \tag{6}$$

where $\lambda(\mathbf{x}_i'\boldsymbol{\beta}/\sigma_v) = \phi(\mathbf{x}_i'\boldsymbol{\beta}/\sigma_v)/\Phi(\mathbf{x}_i'\boldsymbol{\beta}/\sigma_v)$ is the ratio of the standard normal density and distribution functions – the inverse Mills Ratio (Cameron and Trivedi, 2005).

Any dependence of propensity to respond on satisfaction ($\gamma \neq 0$) will imply that the selection term is not zero unless the errors in the response and satisfaction models are perfectly correlated with ($\varepsilon_i = -\gamma u_i$). Since $\lambda(\mathbf{x}_i'\boldsymbol{\beta}/\sigma_v)$ is correlated with $\mathbf{x}_i$, an OLS estimate $\hat{\boldsymbol{\beta}}_2^{OLS}$ of the effects of the observable factors on satisfaction which does not correct for the selection of respondents will be biased: plim $\hat{\boldsymbol{\beta}}_2^{OLS} \neq \boldsymbol{\beta}_2$.

Population and respondent mean satisfaction for the population are

$$\bar{s}^{*pop} = \bar{\mathbf{x}}^{pop\prime}\boldsymbol{\beta}_2 \tag{7}$$

$$\bar{s}^{*resp} = \bar{\mathbf{x}}^{resp\prime}\boldsymbol{\beta}_2 + \left[\textstyle\sum_{i|r_i^* > -\mathbf{x}_i'\boldsymbol{\beta}} K(\mathbf{x}_i'\boldsymbol{\beta})\right]/n^{resp} = \bar{\mathbf{x}}^{resp\prime}\boldsymbol{\beta}_2 + \bar{K}^{resp} \tag{8}$$

where $\bar{\mathbf{x}}^{pop}$, $\bar{\mathbf{x}}^{resp}$ are the means over the population and respondents of the factors determining satisfaction and n^{resp} is the number of respondents. Hence the bias in estimating the mean population satisfaction by the mean of respondent satisfaction is

$$\text{Bias} = \bar{s}^{*resp} - \bar{s}^{*pop} = \underbrace{\left(\bar{\mathbf{x}}^{resp} - \bar{\mathbf{x}}^{pop}\right)'\boldsymbol{\beta}_2}_{\text{selection on observables}} + \underbrace{\bar{K}^{resp}}_{\substack{\text{selection on}\\ \text{unobservables}\\ \text{(response bias)}}} \tag{9}$$

or since $\bar{s}^{*resp} = \bar{\mathbf{x}}^{resp\prime}\hat{\boldsymbol{\beta}}_2^{OLS}$

$$\text{Bias} = \underbrace{\left(\bar{\mathbf{x}}^{resp} - \bar{\mathbf{x}}^{pop}\right)'\boldsymbol{\beta}_2}_{\text{selection on observables}} + \underbrace{\mathbf{x}^{resp\prime}\left(\hat{\boldsymbol{\beta}}_2^{OLS} - \boldsymbol{\beta}_2\right)}_{\substack{\text{selection on unobervables}\\ \text{(response bias)}}} \tag{10}$$

The direction of the bias due to selection on unobservables $\bar{K}^{resp}$ is determined by the sign of $\sigma_{uv} = \gamma\sigma_u^2 + \sigma_{u\varepsilon}$. Thus if $\sigma_{u\varepsilon}$ is small relative to $\gamma\sigma_u^2$, selection on unobservables tends to reduce the respondent mean satisfaction if those who are less satisfied have a lower propensity to respond ($\gamma < 0$).

Now consider the bias due to selection on observables. The difference between the respondent and population means of the explanatories is

$$\overline{\mathbf{x}}^{resp} - \overline{\mathbf{x}}^{pop} = \overline{\mathbf{x}}^{pop} + E\left[\mathbf{e}_i \middle| r_i^* > 0\right] - \overline{\mathbf{x}}^{pop} = E\left[\mathbf{e}_i \middle| r_i^* > 0\right] \tag{11}$$

where $\mathbf{e}_i = \mathbf{x}_i - \overline{\mathbf{x}}^{pop}$. Now

$$E\left[\mathbf{e}_i \middle| r_i^* > 0\right] = E\left[\mathbf{e}_i \middle| v_i > -\mathbf{x}_i'\boldsymbol{\beta}\right] = E\left[\mathbf{e}_i \middle| v_i + \mathbf{e}_i'\boldsymbol{\beta} > -\overline{\mathbf{x}}^{pop\prime}\boldsymbol{\beta}\right] \tag{12}$$

Let $z_i \equiv v_i + \mathbf{e}_i'\boldsymbol{\beta} = \gamma u_i + \varepsilon_i + \mathbf{e}_i'\boldsymbol{\beta}$. If the explanatories $\mathbf{x}$ are jointly normally distributed, then e_{ji} is jointly normal with z_i, and

$$e_{ji} = \frac{\sigma_{x_j z}}{\sigma_z^2} z_i + \omega_{ji} = b_{x_j z} z_i + \omega_{ji}, \quad E\left[\omega_{ji} \middle| z_i\right] = 0 \tag{13}$$

$$\sigma_{x_j z} = \gamma \sigma_{x_j u} + \sigma_{x_j \varepsilon} + \textstyle\sum_k \sigma_{x_j x_k} \beta_k \tag{14}$$

So that

$$E\left[e_{ji} \middle| r_i^* > 0\right] = b_{x_j z} \sigma_z \lambda(\overline{x}^{pop\prime}\boldsymbol{\beta} / \sigma_z) \tag{15}$$

The bias due to selection on observables is

$$\left(\overline{\mathbf{x}}^{resp} - \overline{\mathbf{x}}^{pop}\right)' \boldsymbol{\beta}_2 = E\left[\mathbf{e}_i' \middle| z_i > -\overline{\mathbf{x}}^{pop\prime}\boldsymbol{\beta}\right]\boldsymbol{\beta}_2 = \mathbf{b}_{xz}'\boldsymbol{\beta}_2 \sigma_z \lambda(\overline{\mathbf{x}}^{pop\prime}\boldsymbol{\beta} / \sigma_z) \tag{16}$$

If the j'th variable determines satisfaction, has no effect on response propensity, is independent of all other variables in the satisfaction and response models and of the error ε in the response model, then

$$\sigma_{x_j z} = \sigma_{x_j}^2 \beta_j = \sigma_{x_j}^2 \gamma \beta_{2j} \tag{17}$$

If the variable increases satisfaction ($\beta_{2j} > 0$) and satisfaction reduces response propensity ($\gamma < 0$), then $b_{x_j z} < 0$ and $\overline{x}_j^{resp} < \overline{x}_j^{pop}$. Individuals with higher x_j are more satisfied and therefore less likely to respond, so that the respondent mean of x_j is less than the population mean. Hence, since the variable increases satisfaction, the observable selection on this variable will reduce respondent mean satisfaction. Notice that if the variable reduced satisfaction, we would have $\overline{x}_j^{resp} > \overline{x}_j^{pop}$, but selection on this variable would still reduce reported mean satisfaction. In this very simple case, the fact that satisfaction reduces the propensity to respond always leads to selection on observables reducing mean reported satisfaction. However, (14) shows that in general the respondent mean of a variable may be larger or smaller than the population mean, irrespective of its effect on satisfaction, and so selection on observables may increase or reduce mean reported satisfaction.

The direction of bias due to selection on observables is indeterminate in general. Determining the direction of bias due to selection on unobservables requires fewer assumptions or information: if the covariance between the errors in the response and satisfaction models $\sigma_{u\varepsilon}$ is small relative to $\gamma\sigma_u^2$, then the direction of bias depends on the sign of γ, with the bias being negative if satisfaction reduces propensity to respond.

We may also be interested in how population mean satisfaction changes in over time in response to say policies to increase the income of the workforce or in how it differs across labour markets with different structural features. Even though the mean of reported satisfaction is a biased estimate of the population mean, what are the circumstances under which temporal or cross market differences in reported satisfaction are reasonable estimates of the population mean changes or differences?

Suppose that all individuals in the population experience the same increase in some variable j, thereby increasing the population mean of the variable by the same amount. If the bias is unchanged then the change in mean reported satisfaction is an unbiased estimate of the change in population satisfaction. The bias due to selection on observables (16) changes at the rate

$$\begin{aligned}\frac{\partial\left(\bar{\mathbf{x}}^{resp}-\bar{\mathbf{x}}^{pop}\right)'\boldsymbol{\beta}_2}{\partial \bar{x}_j^{pop}} &= -\mathbf{b}'_{ez}\boldsymbol{\beta}_2\sigma_z\lambda(\bar{\mathbf{x}}^{pop\prime}\boldsymbol{\beta}/\sigma_z)\left(\frac{\bar{\mathbf{x}}^{pop\prime}\boldsymbol{\beta}}{\sigma_z}+\lambda(\bar{\mathbf{x}}^{pop\prime}\boldsymbol{\beta}/\sigma_z)\right)\frac{\beta_j}{\sigma_z}\\ &= -\left(\bar{\mathbf{x}}^{resp}-\bar{\mathbf{x}}^{pop}\right)'\boldsymbol{\beta}_2\left(\frac{\bar{\mathbf{x}}^{pop\prime}\boldsymbol{\beta}}{\sigma_z}+\lambda(\bar{\mathbf{x}}^{pop\prime}\boldsymbol{\beta}/\sigma_z)\right)\frac{\beta_j}{\sigma_z} \qquad (18)\end{aligned}$$

where we use the fact that $\lambda'(w)=-\lambda(w)[w+\lambda(w)]<0$ (Cameron and Trivedi, 2005). Thus if the bias due to selection on observables is negative, the absolute magnitude of the bias is increased by increases in $\bar{x}_j^{pop}$ if $\beta_j < 0$, as would be the case if the variable has no direct effect on response ($\beta_{1j} = 0$) , increases satisfaction ($\beta_{2j} > 0$), and more satisfied individuals are less likely to respond ($\gamma < 0$).

The increase in x_{ji} changes the individual selection terms in (8) at the rate

$$\begin{aligned}\frac{\partial K(\mathbf{x}_i'\boldsymbol{\beta})}{\partial x_{ji}} &= -b_{uv}\sigma_v\lambda(\mathbf{x}_i'\boldsymbol{\beta}/\sigma_v)\left(\frac{\mathbf{x}_i'\boldsymbol{\beta}}{\sigma_v}+\lambda(\mathbf{x}_i'\boldsymbol{\beta}/\sigma_v)\right)\frac{\beta_j}{\sigma_v}\\ &= -K(\mathbf{x}_i'\boldsymbol{\beta}/\sigma_v))\left(\frac{\mathbf{x}_i'\boldsymbol{\beta}}{\sigma_v}+\lambda(\mathbf{x}_i'\boldsymbol{\beta}/\sigma_v)\right)\frac{\beta_j}{\sigma_v} \qquad (19)\end{aligned}$$

Suppose x_j variable has no direct effect on response ($\beta_{1j} = 0$) , increases satisfaction ($\beta_{2j} > 0$) , and more satisfied individuals are less likely to respond ($\gamma < 0$). Then, if $b_{uv} < 0$ so that the bias from selection on unobservables is negative, the increase in x_j also increases the absolute magnitude of the bias due to selection on unobservables.

In general however the effect of changes in the factors affecting satisfaction on the bias in estimating mean population satisfaction as the mean respondent satisfaction is indeterminate. Thus it is not in general true that estimates of changes in mean population satisfaction by changes in mean respondent satisfaction are less subject to bias than estimates of the level of population mean satisfaction.

3 Data

The data are from two rounds of the cross-sectional National Primary Care Research and Development Centre GP Worklife Surveys. We concentrate on the data from the 2005 round but use 2004 to examine bias in estimating changes in GP population job satisfaction. The 2005 sample was a random 5% sample of all National Health Service

GPs in England as recorded in the General Medical Statistics census at 1 October 2004. The postal questionnaire was distributed in the autumn of 2005 and usable data was received from 721 GPs (a 45% response rate).

The questionnaire asked GPs about job satisfaction, their personal characteristics such as ethnicity, family circumstances, their hours worked, their income, and their views on local amenities including schooling and housing. In addition, we had information from the GMS GP census for the entire population of 32,267 GPs on gender, age, part-time status, country of qualification, and on the characteristics of their practice including the number of GPs, the number of and demographic structure of registered patients, local wage rates, and imputed patient population characteristics measuring morbidity and income deprivation.

Overall job satisfaction was measured using the Warr, Cook and Wall (1979) scale. GPs were asked "Taking everything into consideration, how do you feel about your job?". There were seven response categories, with category 1 being labelled "Extreme dissatisfaction" and category 7 labelled "Extreme satisfaction". The Warr-Cook-Wall scale has been used extensively in studies of GP job satisfaction (see Figure 1) and for other groups of workers.

4 Estimation

4.1 Mean population job satisfaction

We first examine the implications of response bias for estimates of the mean satisfaction of the population of GPs based on the mean satisfaction of respondents. We have data from the GP census on the entire population of GPs and can therefore use it to correct for selection on observables by including GP census variables in regressions of reported satisfaction estimated on the set of respondents.

We use two models of job satisfaction. The first treats the numerical labels (1 to 7) on the categories of reported job satisfaction as continuous cardinal variables and estimates OLS models of job satisfaction. We then combine the coefficients $\boldsymbol{\beta}^{OLS}$ from these models with information on the population means of the census variables to produce estimates of population mean satisfaction $\bar{\mathbf{x}}^{pop\prime}\boldsymbol{\beta}^{OLS}$, which corrects for the observable differences between the respondents and the population.

To allow for response bias we estimate a Heckman selection correction model on all sampled GPs in which response is modelled a probit to produce estimates of the inverse Mills ratio $\lambda(\mathbf{x}_i'\boldsymbol{\beta}/\sigma_v)$ which is used in the model of satisfaction conditional on response.

Because the Mills ratio is essentially linear for much of its range there is some debate in the literature (REFs) on whether the Heckman selection model is identified. We improve the identifiability of the selection correction model by including a variable which plausibly affects response but not GP job satisfaction in 2005. The GP sample was drawn from the October 2004 GP census. The questionnaire was administered in the autumn of 2005. We use the October 2005 GP census to see if the GPs sampled had moved practices between October 2004 and October 2005. GPs who move are less likely to respond to the questionnaire since their original practice may not forward the questionnaire. Changing practice is a good instrument for propensity to respond if it also uncorrelated with job satisfaction in the new practice. This may be because GPs move when their job satisfaction in their current practice falls sufficiently far below what they believe to be an acceptable level. The average job satisfaction of movers in their new practice will therefore be equal to the average job satisfaction of GPs in practices with similar GP census characteristics.

We use the selection corrected estimated coefficients on the GP census variables to compute the expected population satisfaction as $\bar{\mathbf{x}}^{pop\prime}\boldsymbol{\beta}^{Heck}$. We can then estimate the bias in estimating mean population satisfaction using the uncorrected mean satisfaction of respondents and can decompose the bias into parts due to selection on observables and on unobservables:

$$\bar{s}^{resp} - \hat{\bar{s}}^{pop} = \bar{\mathbf{x}}^{resp}\hat{\boldsymbol{\beta}}_2^{OLS} - \bar{\mathbf{x}}^{\prime pop}\hat{\boldsymbol{\beta}}_2^{Heck} = \underbrace{\left(\bar{\mathbf{x}}^{resp} - \bar{\mathbf{x}}^{pop}\right)'\hat{\boldsymbol{\beta}}_2^{Heck}}_{\text{selection on observables}} + \underbrace{\mathbf{x}^{resp\prime}\left(\hat{\boldsymbol{\beta}}_2^{OLS} - \hat{\boldsymbol{\beta}}_2^{Heck}\right)}_{\substack{\text{selection on unobervables} \\ \text{(response bias)}}} \quad (20)$$

The second model of job satisfaction that we estimate recognises that satisfaction is a latent variable and we only observe the response categories $s_i = 1,\ldots,7$ as

$$s_i = \ell \text{ if } \mu_{\ell-1} < s_i^* < \mu_\ell, \quad \text{for } \ell = 1,2,\ldots,7, \quad \mu_0 = -\infty, \mu_7 = +\infty \quad (21)$$

Analogously with the linear model, we use the GP census variables to estimate both a standard ordered probit satisfaction model and also estimate the standard ordered satisfaction model simultaneously with a probit response model using a maximum likelihood Stata routine written by the authors. This is an extension of the sample selection corrected probit model developed by Van de Ven and Van Praag (1981). The joint log-likelihood function is given by:

$$LL = \sum_{i|r_i^* \le 0} \ln \Phi(-\mathbf{x}_i' \boldsymbol{\beta}) + \sum_{i|r_i^* > 0} \ln[\Phi_2(a_{\ell i}, \mathbf{x}_i' \boldsymbol{\beta}, -\rho) - \Phi_2(a_{\ell i-1}, \mathbf{x}_i' \boldsymbol{\beta}, -\rho)] \quad (22)$$

where Φ_2 is the bivariate normal CDF, $a_{\ell i} = \mu_\ell - \mathbf{x}_i' \boldsymbol{\beta}_2$ and ρ is the correlation coefficient between the errors u,v in the satisfaction and response equations.

We use the coefficients from these models to estimate the predicted probability of the job satisfaction categories for every individual respondent, take the average of the category probabilties over respondents and apply these averages to the numerical category labels to calculate the expected mean satisfaction level for respondents. As is usually, though not invariably (Lien, 1986), the case with ordered probit models the average probability of each category are very close to the relative frequency of the category in the respondents, so that the mean respondent satisfactions calculated from the ordered probit coefficients are very similar to the actual mean reported satisfaction $\bar{s}^{*resp}$. We then apply the coefficients from the standard ordered probit and selection corrected ordered probit to the GP census variables for the entire population to generate estimates of the mean population satisfaction.

We can then use the respondent and population means to calculate the bias and decompose it into parts due to selection on observables and unobservables:

$$\hat{\bar{s}}_{OP}^{resp} - \hat{\bar{s}}_{OPSC}^{pop} = \underbrace{\hat{\bar{s}}_{OPSC}^{resp} - \hat{\bar{s}}_{OPSC}^{pop}}_{\text{selection on observables}} + \underbrace{\hat{\bar{s}}_{OP}^{resp} - \hat{\bar{s}}_{OPSC}^{resp}}_{\substack{\text{selection on unobervables} \\ \text{(response bias)}}} \tag{23}$$

where the subscripts OP and OPSC indicate whether the estimates of mean satisfaction are based on selection corrected ordered probit.

We repeat the procedure using data from the 2004 GP Worklife Survey and the 2004 GP census to investigate whether estimates of the change in mean population satisfaction are subject to response bias.

4.2 Determinants of job satisfaction

The GP worklife survey contains a rich set of variables which might be expected to influence job satisfaction, including income, hours worked, ethnicity, and family circumstances. We therefore use the information provided by respondents in addition to their GP census characateristics, to examine the determinants of job satisfaction and to see if the qualitative estimated effects of explanatory variables are affected by the model (linear versus ordered probit) or by making allowance for potential response bias using the Heckman selection correction or by simultaneous maximum likelihood estimation of the ordered probit satisfaction and probit response models.

5 Results

Table 1 has the summary statistics for the GP census and GP worklife survey variables 2005. The mean satisfaction of respondents in 2005 of 5.27 is similar to the average reported satisfaction for the workforce as a whole based on the BHPS (Rose, 2005). Comparison of Figure 1 and the BHPS trend from 1992 to 2000 (Rose, 2005, Table 2) suggests that GP mean satisfaction is both more variable over time than for the workforce as a whole and does not exhibit the same downward trend.

GPs in 2005 worked on average 39 hours per week and earned an average annual income of £87,000.[1] Women accounted for 38% of those sampled and 12% of respondent GPs classified themselves as non-white.

5.1 Estimates of mean GP satisfaction

Table 2 reports the results from the linear regressions of job satisfaction on the GP census variables available for all GPs (respondents, non-respondents, and the non-sampled). The first two models are estimated on the full set of GP census variables. The second two

[1] Based on midpoints of earnings brackets assuming that GPs who make less than £25k earn £12.5k and that GPs who make more than £150k earn £175k

models in the table are estimated on a restricted set of explanatory variables after dropping variables with t stats below 1, though we retain the part-time variable because of its intrinsic interest as a rough measures of hours worked. Table 3 reports standard ordered probit and simultaneous ordered probit results for the same two sets of variables. Robust standard errors are reported for the OLS and standard ordered probit estimates. Wald tests indicate that variables omitted from the nested down models are jointly insignificant in all cases.

The pattern of coefficients on the GP census variables is similar in Tables 2 and 3 and has a plausible rationale: for example satisfaction exhibits the familiar U shape in age. We defer a fuller discussion of the determinants of job satisfaction to the next section where report the results of the models which include the richer set of survey variables as well. Our focus here is on the estimation of mean satisfaction and the effects of corrections for selection on observables and unobservables.

The strong inverse relationship between response rates and mean reported satisfaction across the surveys of doctors illustrated in Figure 1 suggests, though as section 2 established it does not prove, that job satisfaction negatively affects propensity to respond. We also find in Tables 2 and 3 that many, though not all, of the factors which affect job satisfaction have the opposite effect on propensity to respond. This again is consistent with, but does not prove, that the more satisfied are less likely to respond. The satisfaction model gives us estimates of the effect of a variable on satisfaction (β_{2j}) and the response model estimates $\beta_j = \beta_{1j} + \gamma\beta_{2j}$ but we still have only one equation to determine the two unknowns β_{1j} and γ.

The Mills ratios in the full and nested down models in Table 2 are not statistically significant at conventional levels but they have t-stats of -1.54 and -1.43 and the correlations between the errors in the response and satisfaction models are -0.76 and -0.70. In the selection corrected ordered probit models in Table 3 the correlations between the errors are rather smaller and also not significant: -0.51 (t-stat -1.65) and -0.45 (t-stat -1.34).

Table 4 shows the estimated mean satisfaction level for the respondents and the population based on the unadjusted and selection adjusted linear and ordered probit models for the full and nested down variable sets. Table 5 uses the information in Table 4 to show the decomposition of the difference between the mean satisfaction of respondents estimated with selection correction and the mean satisfaction of the population estimated from selection corrected models. The selection corrected linear models yield rather larger estimates of population mean satisfaction (6.35 and 6.23) than the selection corrected ordered probit (5.77 and 5.70) but both show a non-trivial difference from the uncorrected mean of reported satisfaction of 5.27. Even with the ordered probit models the effect of correction for selection on observables and unobservables combined is of the same order of magnitude as the temporal changes in mean English GP respondent satisfaction shown in Figure 1.

Table 5 suggests that selection on observables is not a serious problem: in all cases difference in mean satisfaction between respondents and the population estimated with a given set of model coefficients (corrected for selection on unobserverables or not) is very small. The main contribution to the estimated bias is from selection on unobservables which accounts for at least 90% of the estimated bias.

We repeated the analysis using the 2004 GP survey (detailed results available on request). Uncorrected mean respondent satisfaction in 2004 was 4.64. When there was no correction for selection Wald tests suggested that the nested down models were preferred to the full models but for the selection corrected linear and ordered probit models the variables omitted were jointly significant, so that the full models were preferred. The estimates of the correlations between the errors in the response and satisfaction equations were very small, suggesting no bias from selection on unobservables. The Heckman selection corrected estimates of respondent and population mean satisfaction based on the full model were 4.71 and 4.73. The respondent and population means from the ordered probit selection corrected models estimated on the full models were 4.66 and 4.67. Thus the selection corrections made essentially no difference to the estimated means for 2004 satisfaction.

Table 6 reports the effects of correcting for selection on observables and unobservables on the difference in mean satisfaction between 2004 and 2005. The difference between the uncorrected 2005 respondent mean and the uncorrected 2004 mean satisfaction is 0.63. The differences between the uncorrected 2005 and 2004 mean satisfactions are between 0.57 and 0.62. However, because the selection corrections have very little effect in 2004, but were sizable in 2005 and in the same direction as the uncorrected changes, the estimated change in the selection corrected means between 2004 and 2005 are much larger, between 1.00 and 1.51. Thus selection correction also affects the estimated change in mean satisfactions between 2004 and 2005, as well as the levels of mean satisfaction in 2005.

5.2 Determinants of GP satisfaction

Table 7 has the results from regressions of satisfaction on the GP survey variables as well as the GP census variables, after dropping variables with t values under 1 in the satisfaction model, but retaining the gender variable because of its intrinsic interest. The results from the models estimated with the full sets of GP survey and census variables are similar and are available on request.

Selection correction has no effect on the qualitative pattern of coefficients and in most cases only a small effect on their magnitude. The changes in the coefficients as a percentage of the uncorrected coefficients is generally larger in the ordered probit model than in the linear model. None of the coefficients change sign. In most cases negative coefficients become more negative and positive coefficients are reduced. The largest changes are for variables (female, GPs per patient, age, age squared) which are statistically significant in the selection model.

Although female and non-white GPs are less satisfied the coefficients are not statistically significant. Family circumstances (marital status, whether partner works, number of children under 18) had t stats of under 1 in the full model and were dropped from the nested down models shown in Table 7. The only personal characteristics to have a statistically significant effect are age and self assessed health. Satisfaction exhibiting the U shaped relationship against age found in most other studies of job satisfaction, declining with age up to 42 years. GPs in fair health (relative to good health) are less satisfied and those with not good health are even less satisfied.

Income and hours have the expected effects, though hours worked has a surprisingly small negative effect on satisfaction. The coefficients in the linear models suggest that working an additional 10 hours per week with income unchanged, would only reduce satisfaction by 0.1 points.

Working in a dispensing practice is associated with higher job satisfaction. GPs in dispensing practices have higher incomes from the practice profits on dispensing drugs to patients who have no convenient pharmacy. Income is also included in the regression but as the income bands are quite wide, the dispensing variable may be picking up within band income variations. It may also reflect the fact that practices with patients to whom they dispense tend to be located in more rural areas.

GPs in practices with more GPs per 1000 patients are significantly more satisfied. The effect is not due to GPs in practices with a higher GP/patient ratio being able to enjoy more leisure since we control for hours worked. The higher job satisfaction must arise from GPs being better able to use their work time in ways which increase satisfaction. They may be able to provide longer and hence higher quality consultations. Or they may take more on the job leisure.

6 Conclusions

The strong inverse relationship between response rates and mean reported satisfaction in surveys of doctors suggests, though it does not prove, that job satisfaction affects propensity to respond. We also find that many, though not all, of the factors which affect job satisfaction have the opposite effect on propensity to respond. This again is consistent with, but does not prove, that the less satisfied are more likely to respond.

But, whether or not satisfaction affects response, we have shown that simple estimates of mean satisfaction from job satisfaction surveys should be treated with caution. Respondents are not a random sample of the population: they have different observable and unobservable characteristics. Most studies of doctor satisfaction compare the observable characteristics of the respondents and the population and conclude that the differences are small, so that the respondent mean provides a reasonable estimate of the population mean. Some attempt to correct for differences in observable characteristics by regressing job satisfaction on observables and then applying the estimated coefficients to population characteristic means. In the 2005 GP survey we examined suggests that differences in observable characteristics only lead to a small amount of bias. But differences in unobservable characteristics were more important. Correcting for both types of difference increased the estimate of mean job satisfaction by around 0.4 to 1.0 from an uncorrected sample mean of 5.3. Of this around 90% was due to differences in unobservable characteristics. We also found that allowing for selection increased the change in mean satisfaction between 2004 and 2005 by between 0.6 to 1.0. Studies of job satisfaction therefore need to take formal account of the factors determining response and to use methods which attempt to allow for unobservable factors affecting both response and satisfaction. If, as seems plausible, satisfaction affects response, it is inevitable that unobserved factors affecting satisfaction will affect response, and so estimates of mean satisfaction which fail to allow for selection on unobservables will produce biased estimates of mean satisfaction.

We found that response bias, had much less of an effect on the estimates of the effects of observable factors, such as income and hours worked, on job satisfaction. The qualitative pattern of signs and significance of coefficients was unaffected. However the magnitudes of a minority of coefficients, some of them, such as patients per GP of policy relevance such as patients per GP were sensitive to selection correction. Thus, whether the interest is in monitoring the average job satisfaction of GPs or in examining the factors affecting satisfaction, studies of job satisfaction should model response as well as satisfaction.

References

Akerlof G.A., Rose A.K., Yellen J.Y. (1998) Job switching and job satisfaction in the U.S. Labour Market. *Brookings Papers on Economic Activity*, 2, 495-582.

Cameron A.C., Trivedi P. K. (2005). *Microeconometrics: Methods and Applications*. Cambridge University Press, Cambridge

Clark A.E. (2001). What really matters in a job? Hedonic measurement using quit data. *Labour Economics*, 8, 223-242.

Clark A.E., Georgellis Y., Sanfey P. (1998). Job satisfaction, wage changes and quits: evidence from Germany. *Research in Labour Economics*, 17: 95-121.

Clegg, C.W. (1983). Pyschology of employee lateness, absence and turnover: a methodological critique and an empirical study. Journal of Applied Pyschology, 68, 88-101.

Cooper, C.L., Rout, U., Faragher, B. (1989). Mental health, job satisfaction, and job stress among general practitioners. *British Medical Journal*, 298, 366-370.

Davis K., Collins K.S., Schoen C., Morris C. (1995). Choice matters: enrollees' views of their health plans. *Health Affairs*,14, 99-112.

DeVoe, J., Fryer, G.E., Hargraves, J.L., et *al.* (2002). Does career dissatisfaction affect the ability of family physicians to deliver high-quality patient care? *Journal of Family Practice*, 53, 223-228.

French, F., Needham, G., Walker, K., Scott, A. (2003). *Towards a Flexible Workforce - A Basis for Change?* Final Report to NHS Education for Scotland. Aberdeen. NHS Education for Scotland North Deanery. Referenced in French et al (2006).

French, F., Andrew, J., Awramenko, M., Coutts, H., Leighton-Beck, L., Mollison, J., Needham, G., Scott, A., Walker, K. (2006). Why do work patterns differ between

men and women GPs? *Journal of Health Organization and Management*. 20, 163-172.
French, F., Geue, C., Ikenwilo, D., Needham, G., Rooke, C., Skåtun, D., Sutton, M. (2006) *Changes in Job Satisfaction, Work Commitments and Attitudes to Workload following Contractual Reform*. Report to Scottish Executive Health Department. http://www.abdn.ac.uk/heru/publications/reports/2006.php accessed 14 December 2007.
Grol, R., Mokkink, H., Smits, A., Van Eijk, J., Mesker, P., Mesker-Niesten, J. (1985). Work satisfaction of general practitioners and the quality of patient care. *Family Practice*, 2, 128-35.
Laband, D., Lentz, B. (1998). The effects of sexual harassment on job satisfaction, earnings, and turnover among female lawyers. *Industrial and Labour Relations Review*, 51, 594-607.
Lien, D. (1986). Predicted and actual frequencies in binomial response models. *Economics Letters*, 20, 49-51.
Linn, L.S., Yager, J., Cope, D., Leake, B. (1985). Health status, job satisfaction, job stress, and life satisfaction among academic and clinical faculty. *Journal of the American Medical Association*, 254, 2775-2782.
Melville, A. (1980). Job satisfaction in general practice: implications for prescribing. *Social Science and Medicine*, 14a, 495-499.
Rose, M. (2005). Job satisfaction in Britain: coping with complexity. *British Journal of Industrial Relations*, 43; 455-467.
Shields, M.A., Ward, M. (2001). Improving nurse retention in the National Health Service in England: the impact of job satisfaction on intentions to quit. *Journal of Health Economics*, 20, 677-701.
Sibbald, B., Bojke, C., Gravelle, H. (2003). National survey of job satisfaction and retirement intentions among general practitioners in England. *British Medical Journal*, 326, 22-26.
Sibbald, B., Enzer, I., Cooper, C., Rout, U., Sutherland, V. (2000) GP job satisfaction in 1989, 1990 and 1998: lessons for the future? *Family Practice*, 17, 364-71.
Simoens, S., Scott, A., Sibbald, B. (2002). Job satisfaction, work-related stress, and intentions to quit of Scottish GPs. *Scottish Medical Journal*, 47, 480-486.
Van de Ven, W.P.M.M., Van Praag, B.M.S. (1981) The demand for deductibles in private health insurance: A probit model with sample selection. *Journal of Econometrics*, 17, 229-252.
Warr, P., Cook J., Wall, T. (1979). Scales for the measurement of some work attitudes and aspects of psychological well-being. *Journal of Occupational Psychology*, 52: 129-148
Whalley, D., Bojke, C., Gravelle, H., Sibbald, B. (2006). GP job satisfaction in view of contract reform: a national survey. *British Journal of General Practice*, 56, 87-92.
Whalley, D., Gravelle, H., Sibbald, B. (2008). Impact of the new general medical services contract on general practitioners' job satisfaction and perceptions of quality of care in the UK. *British Journal of General Practice*, 58, 8-14

Figure 1. Survey response rates and mean job satisfaction: general practitioners and consultants England and Scotland, 1987 to 2006.

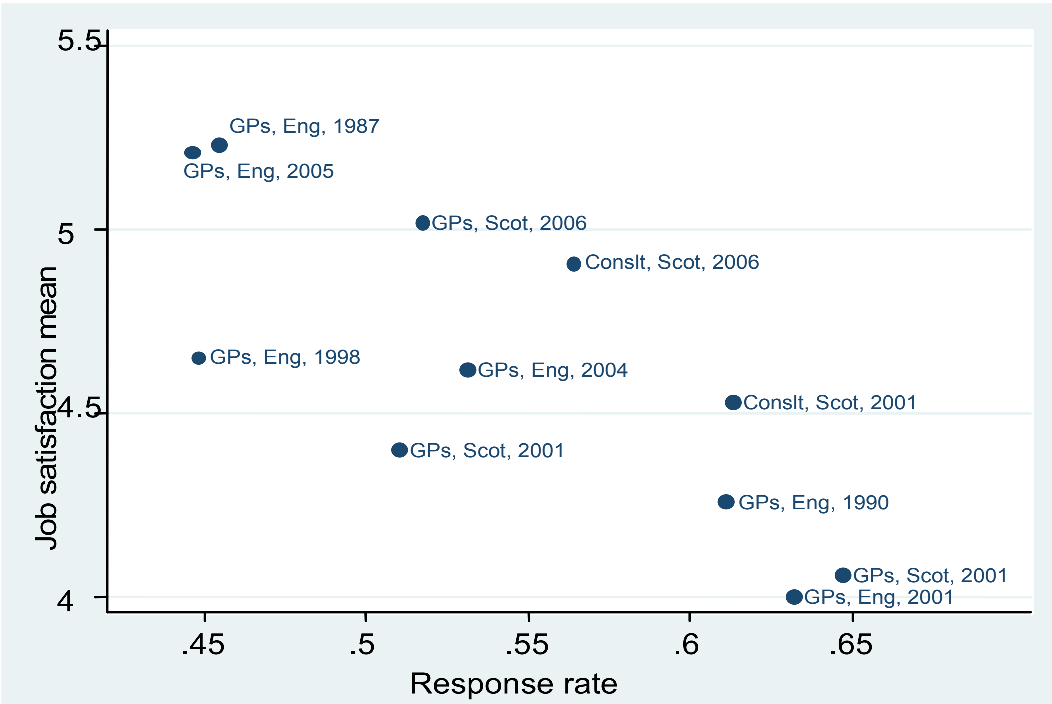

Table 1. Summary statistics

Variable name	Definition	Mean	SD	Min	Max
GMS census variables (1687 observations)					
partt	1 if GP works part-time	0.250		0	1
female	1 if GP is female	0.386		0	1
pms_prac	1 if PMS practice	0.321		0	1
gms_age	Age of GP	46.829	8.891	28	72
dispensing	1 if dispensing practice	0.161		0	1
childhealth	1 if child health practice	0.907		0	1
prop_fem_gps	Proportion of female GPs	0.424		0	1
gps_per_pat	GPs per patient	0.708	0.235	0.106	3.185
tot_patients	Total number of patients	8.826	4.548	0.628	36.388
llti	Limiting long-term illness	98.893	20.901	55.53	182.52
staff_mff	Market forces factor	1.178	0.096	1	1.55
lisi	Low income scheme index	11.294	7.559	1.092	86.931
age_sex	Age-sex payments	2.511	0.225	1.427	3.44
nursres	Nursing home payments	20.198	21.950	0	289.589
moved_prac	1 if GP moved practice	0.023		0	1
GP survey variables (721 observations)					
jobsat	Job satisfaction	5.268	1.220	1	7
non_white	1 if GP is non-white	0.115		0	1
gphrs	Hours worked	38.997	11.664	4	84
callhrs	Hours on call	12.381	11.643	0	72
inc5070	Income £50-70k	0.140		0	1
inc7085	Income £70-85k	0.178		0	1
inc85100	Income £85-100k	0.187		0	1
inc100plus	Income > £100k	0.345		0	1
distance	Commuting distance	5.556	6.327	0	75
high_housep	High houseprice	0.652		0	1
g_school	Good schools	0.589		0	1
fair_health	Fair health	0.211		0	1
notg_health	Not good health	0.028		0	1

Table 2 Overall job satisfaction models using GP census variables only

	OLS		Heck		OLS		Heck	
	coef	t	coef	z	coef	t	coef	z
jobsat								
partt	0.073	0.63	0.112	0.84	0.119	1.04	0.145	1.13
female	-0.157	-1.39	-0.251	-1.80	-0.186	-1.72	-0.305	-2.14
pms_prac	-0.082	-0.80	-0.030	-0.26				
gms_age	-0.121	-2.33	-0.213	-2.49	-0.101	-1.89	-0.183	-2.22
age2	0.001	2.45	0.002	2.57	0.001	2.05	0.002	2.31
dispensing	0.292	2.29	0.357	2.32	0.349	3.02	0.356	2.69
childhealth	0.172	0.94	0.164	0.90				
prop_fem_gps	-0.017	-0.06	-0.276	-0.83				
gps_per_pat	0.663	3.13	0.272	0.77	0.586	3.45	0.359	1.39
tot_patients	0.015	1.30	-0.003	-0.19	0.017	1.52	0.000	-0.02
llti	0.000	-0.02	-0.001	-0.13				
staff_mff	0.392	0.62	0.722	1.04				
lisi	-0.008	-0.73	-0.001	-0.09				
age_sex	-0.123	-0.43	0.008	0.03				
nursres	-0.002	-0.78	-0.002	-0.69				
_cons	7.052	3.80	9.899	3.66	6.758	5.45	9.799	3.87
selection								
partt			-0.024	-0.29			-0.009	-0.11
female			0.112	1.38			0.160	2.16
pms_prac			-0.075	-1.09				
gms_age			0.112	3.20			0.110	3.22
age2			-0.001	-3.39			-0.001	-3.44
dispensing			-0.087	-0.94			-0.010	-0.12
childhealth			-0.008	-0.07				
prop_fem_gps			0.303	1.73				
gps_per_pat			0.561	3.48			0.369	3.21
tot_patients			0.024	3.37			0.026	3.72
llti			0.000	0.08				
staff_mff			-0.450	-1.09				
lisi			-0.008	-1.13				
age_sex			-0.206	-1.04				
nursres			0.000	-0.05				
moved_prac			-1.148	-3.99			-1.166	-4.12
_cons			-2.180	-1.80			-3.052	-3.81
lambda			-1.149	-1.54			-1.032	-1.43
rho			-0.761				-0.705	
N	721		1687		737		1705	

Table 3 Overall job satisfaction models using GP census variables only: ordered probit

	OP		OP selection correction		OP		OP selection correction	
	coef	t	coef	z	coef	t	coef	z
jobsat								
partt	0.043	0.43	0.056	0.58	0.081	0.81	0.086	0.89
female	-0.137	-1.40	-0.166	-1.78	-0.164	-1.80	-0.205	-2.28
pms_prac	-0.069	-0.79	-0.039	-0.46				
gms_age	-0.109	-2.35	-0.141	-2.97	-0.097	-2.05	-0.126	-2.59
age2	0.001	2.51	0.002	3.14	0.001	2.22	0.001	2.77
dispensing	0.302	2.51	0.304	2.71	0.355	3.25	0.335	3.13
childhealth	0.138	0.94	0.122	0.90				
prop_fem_gps	-0.036	-0.16	-0.149	-0.67				
gps_per_pat	0.606	3.16	0.381	1.52	0.520	3.33	0.388	1.91
tot_patients	0.010	1.08	0.002	0.15	0.012	1.28	0.004	0.36
llti	-0.001	-0.23	-0.001	-0.28				
staff_mff	0.246	0.46	0.371	0.75				
lisi	-0.008	-0.81	-0.004	-0.42				
age_sex	-0.208	-0.84	-0.134	-0.57				
nursres	-0.002	-0.97	-0.002	-0.98				
selection								
partt			-0.027	-0.32			-0.011	-0.14
female			0.114	1.41			0.160	2.16
pms_prac			-0.072	-1.04				
gms_age			0.113	3.23			0.110	3.22
age2			-0.001	-3.42			-0.001	-3.43
dispensing			-0.086	-0.93			-0.008	-0.09
childhealth			-0.008	-0.07				
prop_fem_gps			0.299	1.71				
gps_per_pat			0.560	3.49			0.369	3.21
tot_patients			0.024	3.28			0.026	3.67
llti			0.000	0.06				
staff_mff			-0.459	-1.11				
lisi			-0.009	-1.16				
age_sex			-0.217	-1.09				
nursres			0.000	-0.07				
moved_prac			-1.191	-4.18			-1.200	-4.26
_cons			-2.144	-1.77			-3.049	-3.81
rho			-0.511	-1.65			-0.447	-1.34
N	721		1687		737		1705	

Table 4. Estimates of mean GP job satisfaction 2005

(a) estimates from model with full set of GP census variables

		OLS		Heckman		Ordered Probit		Ordered Probit selection correction	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
	N								
Respondents	727	5.268	0.261	6.275	0.291	5.268	0.266	5.726	0.223
Population	32267	5.288	0.282	6.351	0.357	5.288	0.284	5.765	0.284

(b) estimates from model with reduced set of GP census variables

		OLS		Heckman		Ordered Probit		Ordered Probit selection correction	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
	N								
Respondents	737	5.263	0.250	6.168	0.281	5.264	0.252	5.668	0.223
Population	34888	5.300	1.207	6.234	0.795	5.287	0.267	5.702	0.245

Table 5. Decomposition of bias in estimates of mean GP job satisfaction

(a) estimates from models with full set of GP census variables

	OLS Heckman	Ordered Probit selection correction
Selection on observables	-0.076	-0.039
Selection on unobservables	-1.007	-0.458
Total bias	-1.083	-0.497

(b) estimates from models with reduced set of GP census variables

	OLS Heckman	Ordered Probit selection correction
Selection on observables	-0.066	-0.034
Selection on unobservables	-0.905	-0.404
Total bias	-0.971	-0.438

Table 6 Estimates of change in mean GP job satisfaction 2004 to 2005

	OLS	OLS Heckman	OP	OP with selection correction
Respondents	0.621	1.461	0.621	1.007
Population	0.602	1.506	0.565	1.031

Estimates based on OLS and OP are from the nested down models in both years. The selection corrected estimates are from the full models in 2004 and the nested down models in 2005

Table 7. Determinants of GP job satisfaction 2005: allowing for response bias

	OLS		Heck			OP		OP selection correction		
	coef	t	coef	z	% diff in linear coef	coef	z	coef	z	% diff in OP coef
jobsat										
female	-0.046	-0.44	-0.127	-0.93	176.1	-0.052	-0.55	-0.124	-1.35	138.5
partt	0.229	1.81	0.246	1.84	7.4	0.183	1.55	0.167	1.57	-8.7
gms_age	-0.134	-2.5	-0.195	-2.43	45.5	-0.131	-2.65	-0.167	-3.81	27.5
age2	0.002	2.68	0.002	2.5	0.0	0.002	2.86	0.002	4.07	0.0
dispensing	0.297	2.53	0.297	2.43	0.0	0.315	2.69	0.261	2.5	-17.1
gps_per_pat	0.486	3.04	0.352	1.54	-27.6	0.47	2.96	0.257	1.42	-45.3
nursres	-0.003	-1.5	-0.003	-1.4	0.0	-0.004	-1.82	-0.003	-1.67	-25.0
non_white	-0.196	-1.34	-0.189	-1.4	-3.6	-0.181	-1.42	-0.141	-1.34	-22.1
gphrs	-0.011	-2.17	-0.011	-2.15	0.0	-0.011	-2.27	-0.009	-2.11	-18.2
callhrs	-0.007	-1.48	-0.007	-1.74	0.0	-0.004	-1.03	-0.003	-0.99	-25.0
inc5070	0.297	1.79	0.282	1.73	-5.1	0.236	1.58	0.173	1.33	-26.7
inc7085	0.388	2.22	0.380	2.23	-2.1	0.335	2.12	0.267	1.94	-20.3
inc85100	0.593	3.38	0.579	3.15	-2.4	0.5	3.04	0.386	2.39	-22.8
inc100plus	0.885	4.91	0.870	4.83	-1.7	0.793	4.6	0.639	3.72	-19.4
distance	-0.021	-1.77	-0.021	-3.11	0.0	-0.014	-1.46	-0.01	-1.61	-28.6
high_housep	0.163	1.75	0.164	1.82	0.6	0.144	1.68	0.118	1.64	-18.1
g_school	0.145	1.66	0.145	1.67	0.0	0.139	1.71	0.114	1.65	-18.0
fair_health	-0.502	-4.9	-0.502	-4.84	0.0	-0.48	-5.24	-0.407	-4.44	-15.2
notg_health	-1.256	-4.05	-1.260	-4.79	0.3	-0.974	-4.44	-0.838	-3.88	-14.0
_cons	7.756	6.02	9.822	4.19	26.6					
selection										
female			0.156	2.11				0.155	2.09	
partt			-0.007	-0.08				-0.016	-0.19	
gms_age			0.121	3.55				0.12	3.55	
age2			-0.001	-3.83				-0.001	-3.83	
dispensing			0.007	0.08				0.019	0.23	
gps_per_pat			0.326	2.85				0.327	2.86	
nursres			0	-0.2				0	-0.29	
moved_prac			-1.159	-4.13				-1.131	-4.2	
_cons			-2.981	-3.72				-2.966	-3.71	
lambda			-0.715	-1.06						
rho			-0.565					-0.707	-3.28	
N	737		1705			737		1705		