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Abstract

This paper investigates the nature and consequences of sample attrition in a unique longitudinal survey of medical doctors. We describe the patterns of non-response and examine if attrition affects the econometric analysis of medical labour market outcomes using the estimation of physician earnings equations as a case study. We compare the econometric estimates obtained from a number of different modeling strategies: balanced versus unbalanced samples; an attrition model for panel data based on the classic sample selection model; and a recently developed copula-based selection model. Descriptive evidence shows that doctors who work longer hours, have lower years of experience, are overseas trained, and have changed their work location are more likely to drop out. Our analysis suggests that the impact of attrition on inference about earnings of General Practitioners is small. For specialists, the impact of attrition is statistically and economically significant, but is on the whole not very large. Finally we discuss how the top-up samples in the MABEL survey can be used to address the problem of panel attrition.

JEL classification: C23, J31, I11

Keywords: Attrition, medical doctors, earnings, copula

1 Introduction

This paper investigates sample attrition in a unique longitudinal survey of medical doctors. The availability of longitudinal data has allowed researchers on health and health economics to investigate a wide range of research questions that would otherwise not be possible using cross-sectional data. Some examples of longitudinal data on health include social surveys such as the Survey of Health, Ageing and Retirement in Europe (SHARE), and in the form of administrative datasets such population registers, hospital records and insurance reimbursement claims.[1]

A key limitation of longitudinal data is the problem of non-response and attrition. For instance, the long-running Michigan Panel Study of Income Dynamics began in 1968, and lost almost 50 percent of the initial sample members (Fitzgerald et al. 1998) by 1989. The Community Tracking Study, which surveys medical doctors and the general population to investigate the impact of health systems changes, successfully re-interviewed 77 percent of physicians in its second year, with the remaining individuals dropping out largely due to the refusal to respond (Potter et al. 2013). Attrition creates a problem of missing data, and can potentially have serious consequences when researchers use only data of responding individuals (Little and Rubin 1987). Attrition reduces the effective sample size, and limits the ability to observe longitudinal patterns in outcomes of interest. Attrition may also result in attrition bias which may impede the ability to draw valid inference from econometric analysis.

A number of approaches to handle attrition exist, and their use depends on the assumptions made about the origins and causes of the missing data problem. If the data are assumed to be missing at random (MAR), reweighting using post-stratification weights can be used to adjust for the non-response. Alternatively inverse probability weighting can be applied, which involves estimating the probability of response as a function of observed characteristics (Fitzgerald et al. 1998; Jones et al. 2004). If the data is not

[1]See Jones (2007) for an extensive list of longitudinal surveys used in applied research on health economics.

missing at random, attrition may be accommodated by modeling the non-response simultaneously with the outcomes of interest (e.g Hausman and Wise 1979; Wooldridge 2010). These model-based methods usually require strong and often untestable assumptions.

An alternative to weighting and model-based methods is the use of refreshment samples – newly and randomly sampled respondents added at subsequent waves of the panel (e.g. Ridder 1992). These samples can provide additional information about the attrition process, allowing for more robust and precise estimation than relying solely on conventional methods (Hirano et al. 2001).

In this paper, we investigate the nature and consequences of attrition in the Medicine in Australia: Balancing Employment and Life (MABEL) longitudinal survey of doctors. The MABEL survey is unique as it is one of a handful of longitudinal survey of medical doctors worldwide. The survey has become a major research infrastructure and a valuable resource for the analysis of important research questions on the medical labour market.[2] Like all panel studies, the strength of the MABEL survey lies in its longitudinal design, and its usefulness hinges on the sample being representative of the population of doctors in scope. This can potentially be threatened by panel attrition in MABEL, which is relatively serious given that roughly one-third of the original MABEL cohort have dropped out by the end of the fourth year (Yan et al. 2013).

If attrition leads to a random loss of data, then by definition such loss will not lead to sample selection bias. Hence a natural way to investigate the effects of attrition is to design a test of the hypothesis that data has a MAR property. We do so in several ways. We first compare the results from balanced and unbalanced samples, which we would not expect to significantly differ if the MAR assumption is valid. Following a conventional approach we specify a selection model for panel data and test whether there is a statistically significant selection effect. To test some of the potential limitations of this approach we also use a recently developed copula-based framework to test if the conclusions based on the selection model are robust to alternative formulations. MABEL also makes available

[2]See www.mabel.org.au for more information on the objectives of the MABEL survey, and the research and policy publications using the survey. Accessed 26 October 2013.

a top-up sample during each wave after the first, which in turn generates a top-up panel of its own. These additional panels also support further tests of the MAR assumption. Jointly, the various components provide a comprehensive investigation of the importance of attrition.

We investigate if the attrition in the MABEL survey affects the econometric analysis of medical labour market outcomes using the estimation of General Practitioners and medical specialists earnings equations as a case study. The determinants of doctors' earnings were analysed recently by Morris et al. (2011) and Cheng et al. (2011), and have been studied in the context of the effect of earnings on hours worked (e.g. Rizzo and Blumenthal 1994); job satisfaction (Ikenwilo and Scott 2007); the choice of working in the public or private sector (Sæther 2005); and gender differentials (Gravelle et al. 2011). A unifying feature in these studies is the reliance on cross-sectional data. There have been a handful of more recent studies that employed panel data (e.g. Baltagi et al. 2005; Sasser 2005; Andreassen et al. 2013), although none of these studies explicitly considered the effects of attrition.

We focus our attention on the estimate of the elasticity of earnings with respect to hours worked, which have been shown to be an important variable in explaining earnings. For example, Schurer et al. (2012) find that differences in hours worked explain 53 percent of the earnings gap among male and female Australian General Practitioners. An important issue in the earnings differential literature is the question of whether the marginal returns to working hours decreases with the number of hours worked, and this has been analysed for medical doctors (Conrad et al. 2002; Gravelle et al. 2011) as well as solicitors (McNabb and Wass 2006).

Previewing our results, the analysis on the nature of attrition in the MABEL survey shows that doctors who work longer hours, have lower number of years of experience, are overseas trained, and have changed their work location are more likely to drop out. Our analysis suggests that the impact of attrition on inference about earnings of GPs is small. This conclusion applies to both the 2008 cohort and the top-up samples of GPs.

In the case of specialists the impact is statistically and economically significant, but is on the whole not very large for the focus variables. We find no major conflicts between the selection model and copula-based estimates. Finally we discuss how the top-up samples in MABEL survey can be potentially be used to address the problem of panel attrition.

The remainder of the paper is organised as follows. Section 2 describes the MABEL survey and assesses the extent of, and reasons for, sample attrition. Section 3 discusses the estimation strategy for modeling attrition. Section 4 discusses the econometric estimates of the attrition function, and the estimated hours elasticity on doctors earnings using the original 2008 cohort of doctors. Section 5 analyses attrition in the top-up samples in MABEL, and discusses the issues involved in using the top-up samples. Finally, Section 6 concludes with the key findings of the paper.

2 The MABEL Longitudinal Survey of Doctors

The Medicine in Australia: Balancing Employment and Life (MABEL) survey is a longitudinal survey of Australian doctors that began in 2008. The aim of the survey is to investigate factors influencing workforce participation, labour supply, specialty choice, and mobility of doctors. The survey covers four broad groups within the medical workforce: General Practitioners (primary care practitioners); medical specialists; specialists-in-training (e.g. registrars); and hospital non-specialists. The sample frame is the Australian Medical Publishing Company's (AMPCo) Medical Directory, a national database managed by the Australian Medical Association.

The original cohort comprises 10498 doctors working in clinical practice in Australia, representing more than 19 per cent of the clinically active population of Australian doctors in 2008. This cohort was shown to be nationally representative with respect to age, gender, geographic location and hours worked (see Joyce et al. (2010) for a description of the cohort and survey methods). Approximately 80 percent of all doctors in the 2008 cohort are General Practitioners (N=3906) and specialists (N=4596). From the second and subsequent waves, top-up samples comprising mainly of new entrants to the medical workforce are included to maintain the cross-sectional representativeness of the survey. These doctors are predominantly junior doctors: hospital non-specialists and specialists-in-training. The percentage of General Practitioners and specialists in each top-up cohort is approximately 35 percent to 46 percent.[3]

The survey is conducted annually, with invitation letters to participate in the survey distributed by mail through AMPCo in June. Doctors are given the option to complete a paper version of the survey questionnaire which they can return with a reply-paid envelope, or a web-based version. All doctors (original and top-up cohorts) are invited to participate in every subsequent year unless they indicate their intention to opt out of the study. At the time of writing, the sixth wave of the survey is being fielded, with funding secured for an additional three waves (up to 2016).

2.1 Non-response in the MABEL survey

Doctors in each cohort of the MABEL study are defined as responders if they complete a survey questionnaire in any subsequent wave of the survey. Responding doctors can either be in clinical practice or not in clinical practice at the time of the survey. Those not undertaking clinical practice were only asked about their current status (e.g. maternity leave, working outside of Australia) and their intentions on resuming clinical work in Australia. A doctor is a non-respondent in a subsequent wave if he or she fails to complete or return the survey questionnaire. Non-response can arise as a result of the refusal to respond or cooperate; absence of a valid contact address; declining to participate; or death of a study subject. Non-respondents are regarded as having attrite or dropped out from their respective cohorts over the subsequent waves.

Table 1 describes the distribution of responders and attritors among General Practitioners (GPs) and specialists in the 2008 cohort across the first four waves of the MABEL

[3] The total, general practitioner, and specialist sample sizes are as follows. Wave 2: 2124, 495, 348. Wave 3: 1298, 388, 213. Wave 4: 1375,199, 285.

survey. The conditional attrition rate, defined as the ratio of the number of drop-outs in wave t and the number of respondents in wave *t-1*, is highest between the first and second waves. 21.5 percent and 20.2 percent of GPs and specialists respectively in the original cohort did not respond in the second year. By the end of the fourth year, 65.4 percent of GPs and 66.8 percent of specialists remained in the survey, with the cumulative attrition rates of 34.6 and 33.2 percent. The overall survival rate across all four doctor groups (including specialists-in-training and hospital non-specialists) in the 2008 cohort after four years is 65.9 percent (Yan et al. 2013).

A significant fraction of attriting doctors re-enter the study in a subsequent wave. This can be seen from the last column of Table 1, which shows the number of rejoiners – doctors who are non-respondents in wave *t-1* and responded in wave t. Approximately 23 to 32 percent of drop-outs in a previous wave responded to the next wave. A possible explanation for the high rejoiner rate is that changes in work (or residential) address can result in doctors being not contactable. This may arise if the AMPCo database does not have information on the most recent address despite being updated regularly. Correspondingly, these doctors who were previously non-responders are likely to rejoin the survey when their addresses in the database have been updated. Indicative evidence can be observed from the data, where in wave 3, 8.4 percent of those have moved from a different postal area are rejoiners compared with 5.6 percent for those who had not moved. As we will explain in Section 3, it is usual to exclude rejoiners from the econometric analysis.

Table 2 presents the conditional attrition rates by annual earnings and hours worked at wave *t-1*. The attrition patterns suggest that the relationship between attrition, earnings and hours worked, is not straightforward and varies by doctor type. For GPs, attrition rates are lowest for doctors in the first and fifth earnings quintiles. This relationship is reversed for specialists where attrition rates are highest for doctors with the lowest and highest earnings. Given that higher annual earnings can result from doctors working a larger number of hours, or having a high implied hourly earnings rate, attrition rates by annual hours worked are also presented in Table 2 to provide a more complete picture. For both GPs and specialists, the attrition rates are broadly increasing in hours worked suggesting that doctors who work longer hours are more likely to drop out in the subsequent wave.

Table 3 describes how attrition rates differ by doctors' characteristics. For both GPs and specialists, doctors who are male, are less experienced (and younger), self-employed, and have changed postcodes are more likely to drop out across the four waves of the survey. The likelihood of dropping out is also positively associated with the length of time doctors' take to complete and return the survey in the preceding wave.

Below we examine the effects of attrition in the MABEL survey on the analysis of labour market outcomes using the estimation of physician earnings equations as a case study. Before doing so, we first describe the econometric strategy for assessing and accounting for attrition bias. This is discussed in the next section.

3 Econometric Strategy

The literature on panel attrition has several alternative approaches for handling the potential selection biases that might ensue from it. Whether selection bias is a serious concern may well depend upon the variable under study and hence conclusions will necessarily be qualified.

Under the assumption that attrition leads to observations missing at random, we would not expect that the resulting unbalanced sample will generate significantly different estimates from a balanced subsample. A comparison of the two sets of results then can provide a basis of a Hausman-type test for selection bias without having to identify the attrition function (Nijman and Verbeek 1992). In the same spirit, using a refreshment sample if one is available to replace the missing observations with similar ones from the same population will also reduce or eliminate selection bias without having to identify the attrition function (Hirano et al. 2001). Imputation of missing values has a similar objective, but doing so without an attrition function is difficult.

By contrast, the selection model approach requires a well-specified attrition function with a driver instrument which affects attrition but not the outcome ("exclusion restriction"). Panel variants of the selection model have been developed (Wooldridge 2010), and these usually rely on the assumption of joint normality. The more recently developed copula-based approach combines the marginal distributions of attrition and outcome variables. It can avoid the joint normality assumption, and does not require an exclusion restriction to identify the attrition function (Smith 2003; Hasebe 2013). The latter consideration is potentially important because we do not have survey administrative type variables that would serve as instruments. However, copulas do require a potentially sensitive choice of the functional form.

Overall no one approach is uniformly dominant. In this paper we will apply the panel variants of the classic selection model and the copula-based approach. We will also exploit the available top-up samples to check the robustness of our conclusions.

3.1 Selection-based panel attrition model

A standard specification of the attrition model consists of an attrition function and an outcome equation. The attrition function models the propensity for sample attrition using the indicator function $1[A^*_{it} > 0]$, conditional on a vector of observable variables $\mathbf{z}_{it}$, and nonattrition in $t-1$. Formally,

$$A_{it} \equiv 1[A^*_{it} > 0 | \mathbf{z}_{it}, A_{it-1} = 1] = \begin{cases} 1 \text{ if } A^*_{it} > 0 \\ 0 \text{ if } A^*_{it} \leq 0 \end{cases}$$

where A^*_{it} denotes a latent variable. A_{it} takes the value 1 if the subject who responded to the survey questionnaire at $t-1$ does not respond at time t, and takes the value 0 otherwise. The probit regression is a common specification of the attrition function, i.e. $\Pr[A_{it} \equiv 1 | \mathbf{z}_{it}, A_{it-1} = 1] = \Phi[\mathbf{z}'_{it}\gamma]$.

The outcome variable y_{it} is observed at t for all subjects that remain in the sample; in that case the observed outcome y_{it} coincides with the latent outcome y_{it}^*. Formally, the outcome of interest is observed only for subjects that have not attrited from the sample:

$$y_{it} = \begin{cases} y_{it}^* \text{ if } A_{it}^* > 0 \\ - \text{ if } A_{it}^* \leq 0 \end{cases}$$

It is usual to assume that if $A_{it}^* < 0$, then $A_{it+j}^* < 0$, for all $j \geq 1$; that is, once a subject attrites from the sample, then never rejoins and hence its responses are censored. For a subject i, $i = 1, ..., N$, T_i observations are available.

The formal structure of the attrition model for panel data is similar to that of the classic sample selection model:

$$\begin{aligned} A_{it}^* &= \mathbf{z}_{it}'\gamma + \varepsilon_{1it}, \\ y_{it}^* &= \mathbf{x}_{1it}'\beta_1 + \mathbf{x}_{2i}'\beta_2 + \alpha_i + \varepsilon_{2it}, \end{aligned}$$

where α_i denotes the unobserved individual-specific effect, and the equation errors $(\varepsilon_{1it}, \varepsilon_{2it})$ may be correlated. In the two-component vector $(\mathbf{x}_{1it} \;\; \mathbf{x}_{2i})$ the first component $\mathbf{x}_{1it}$ consists of time-varying regressors and the second component $\mathbf{x}_{2i}$ consists of time-invariant regressors. If this correlation is zero, then the pair (A_{it}^*, y_{it}^*) will be uncorrelated, conditional on the observed variables $(\mathbf{z}_{it,}\mathbf{x}_{1it})$ and on individual specific-effect α_i, which may be treated either as a correlated (with the $\mathbf{x}_{1i}$) effect or an uncorrelated effect, a point that will be discussed further below. In such a case the attrition function and the outcome equation are *conditionally* independent; this case will be referred to as one in which attrition leads to data that is MAR. In such a case the outcome equation can be consistently estimated independently of the attrition equation.

In a selection model the random shock, ε_1, which affects the probability of attrition is correlated with the shock ε_2 which affects the outcome. Ignoring this correlation, as when the outcome equation is estimated under the MAR assumptions, results in selection bias. A number of panel data estimators are available for estimating the selection model; see Wooldridge (2010, chapter 19.9). This set includes parametric estimators which assume that $(\varepsilon_{1it}, \varepsilon_{2it})$ have bivariate normal distribution, as well as the semiparametric two-step estimator which makes a sample selection adjustment. As in the case of the classic selection model for cross-section data, robust identification of the parameter β_1 outcome requires that the attrition equation contains some nontrivial regressors that do not directly affect the outcome. One potential difference from the cross-sectional case, however, comes from the possibility that the set of instruments can vary over t.

We assume that the individual specific effect α_i is (a "fixed effect") correlated with the regressors in the outcome equation. To eliminate these fixed effects, we apply a sweep-out transformation to the outcome equation which yields:

$$\widetilde{y}_{it} = \widetilde{\mathbf{x}}'_{1it}\beta_1 + \widetilde{\varepsilon}_{2it},$$

where the tilde notation denotes either the deviations-from-the sample-average ("within") transformation or the first differencing transformation The first-differencing transformation leads to a greater loss of observations since the range of t now starts at $t = 2$. But it also implies some analytical simplicity. Rewriting the above equation in terms of first differences, we have

$$y_{it} - y_{i,t-1} = (\mathbf{x}'_{1,it} - \mathbf{x}'_{1i,t-1})\beta_1 + (\varepsilon_{2,it} - \varepsilon_{2,it-1}).$$

To facilitate two-step estimation of the above equation the error term $\varepsilon_{2,it}$ is expressed in terms of its conditional expectation:

$$\begin{aligned} \varepsilon_{2,it} &= \mathrm{E}[\varepsilon_{2,it}|\varepsilon_{1,it}] + \eta_{it}, \\ &= \sigma_{12}\lambda_{it}(\mathbf{z}'_{it}\gamma) + \eta_{it}, \end{aligned}$$

where η_{it} is an i.i.d. error term and $\lambda_{it}(\mathbf{z}'\gamma)$ denotes the attrition hazard (aka inverse Mills ratio), and σ_{12} denotes the covariance between $(\varepsilon_{1it}, \varepsilon_{2it})$. A consistent estimator of $\lambda_{it}(\mathbf{z}'\gamma)$, denoted $\widehat{\lambda}_{it}$, is generated by the probit equation for the attrition event. Then the equation

$$y_{it} - y_{i,t-1} = (\mathbf{x}'_{1,it} - \mathbf{x}'_{1i,t-1})\beta_1 + \sigma_{12}\widehat{\lambda}_{it} + [\eta_{it} + (\varepsilon_{2,it} - \varepsilon_{2,it-1}) + \sigma_{12}(\lambda_{it} - \widehat{\lambda}_{it})]$$

where the three terms inside the square brackets define the composite error on the outcome equation. Under the assumption that all elements of $\mathbf{x}'_{1,it}$ are uncorrelated with the composite error term the least squares estimator is a consistent estimator. However, as $\widehat{\lambda}_{it}$ is a generated regressor, and, moreover, the structure of the error implies serial correlation as well as heteroskedasticity (given of the presence of $\lambda(\cdot)$ in the composite error term), standard errors and inference should be based on a suitably robustified variance estimator, e.g. a robust panel variance estimator.

The foregoing analysis involves several implicit assumptions which are natural in a cross section sample but which could be relaxed in a panel data setting. For example, it is not necessary to assume that γ is constant across different panel waves. The attrition equation may be estimated for each wave separately, say using the probit specification $\Pr[A_{it}|\mathbf{z}_{it}, A_{i,t-1} = 1] = \Phi(\mathbf{z}'_{it}\gamma_t)$, which in turn would generate the time varying attrition hazard $\Phi(\mathbf{z}'_{it}\gamma_t)$ The outcome equation given above can be generalized to include an estimated λ-term for each wave at the cost of creating a more complicated expression for the error on the equation.

An alternative specification is that in which one or more elements of $\mathbf{x}_{1it}$ is endogenous, in which case an IV or GMM type estimator would be preferred. The usual caveats regarding the choice of instruments will apply and it should be noted that the presence of serially correlated errors will affect both the selection of valid instruments and the appropriate variance estimator.

In the above framework, a test of the null hypothesis of MAR against the alternative of selection bias may be based on $H_0 : \sigma_{12} = 0$ versus $H_1 : \sigma_{12} \neq 0$. Given quite strong assumptions involved in its implementation and the complexity of the robust variance estimator, the outcome of the test should be treated with caution. As mentioned earlier, there are other alternatives for testing this hypothesis, though these too have limitations. The outcome equation could be estimated using inverse probability weights (IPW) - an approach that does not require us to identify the attrition function. But IPW often generates imprecise results. Another approach (Nijman and Verbeek 1992) is to compare results based on balanced and unbalanced panels. While a formal Hausman-type test has been suggested based on such a comparison, the validity of the test is questionable without making strong assumptions. Yet another option which we consider in Section 5 uses a refreshment or a matched top-up sample to replace the missing attritors. Implementation of this approach is not practical for our data set as we explain in Section 5.

3.2 Copula-based approach to selection

This paper's empirical analysis of attrition within the framework of a selection model has three important limitations that apply to this genre of specifications. First, the methodology of controlling for selection relies on the restrictive assumption of bivariate normality. Second, it requires that we have a nontrivial excluded exogenous variable which serves to identify the role of attrition. Third, its test of selection is based only on a linear measure of dependence (correlation) between unobserved factors that simultaneously impact both attrition and earnings.

To address these limitations we also estimated our model using the recently developed copula-based estimator which relaxes the normality assumption and does not need any exclusion restrictions. A fully parametric copula-based approach (based on Sklar's Theorem) requires that we specify the marginal distributions ("margins") of the attrition and earnings variables, denoted $f(A|\bullet)$ and $f(y|\bullet)$ (where conditioning variables are suppressed for notional simplicity) respectively, and then combined using a specified parametric copula, denoted $C[f(A|\bullet), f(y|\bullet), \Theta]$ where Θ is a scalar-valued dependence parameter. This generates a joint distribution of A and y (with a dependence parameter) that may be estimated by maximum likelihood. We estimated the copula selection models using the Stata program *heckmancopula* developed by Hasebe (2013).

The flexibility of the approach comes from the feasibility of varying both the margins, i.e. $f(A|\bullet)$ and $f(y|\bullet)$, and the functional form of the copula, $C[\bullet]$. Further, provided the margins are sufficiently flexible, this approach potentially covers a wider range of dependence structures than possible under normal distribution. Specifically, one can model asymmetric or symmetric tail dependence. Sample selection effect is such a model takes on a more general form.

The advantages of the copula-based approach were mentioned earlier in this section. A limitation of the approach concerns the choice of the copula function out of a set of many possible one. This disadvantage is mitigated if we consider several combinations of copulas and alternative specifications of the marginal distributions and choose the "best" model according to a specified criterion. This is the approach followed. The marginal for attrition, a binary variable, is straight-forward, probit or logit; that for log(income) is more open. We have considered a set of alternatives that includes the lognormal, log-logistic, Student's t. The final choice between these alternative model specifications is based on the penalized log-likelihood criterion. We discuss the details of the exercise in Section 4.

4 Results

4.1 Physician earnings model

The dependent variable of interest in the econometric analysis is the logarithm of annual gross (pre-tax) earnings of GPs and specialists . We examine annual earnings as opposed to hourly wages because an earnings model of hourly wages is misspecified if earnings are not proportional to hours worked (Cheng et al. 2011; Gravelle et al. 2011). Given that total earnings are increasing in working hours, we include annual hours worked an explanatory variable, which is constructed using information on total weekly hours worked, and the number of weeks worked per year.

In addition to hours worked, we include doctors' personal characteristics and a set of human capital variables such as doctors education and professional qualifications, experience, and medical specialty for specialists. Given that employment mode and practice characteristics are likely to influence earnings, we include variables on self-employment, GP practice size and whether they undertake hospital work, and the fraction of time in clinical work by specialists. We also include a set of state and territory indicators and measures of remoteness to control for local area characteristics. The sample characteristics, by attrition status, are presented in Table A.1 in the appendix.

The set of explanatory variables described above are included in the attrition function and the outcome equation. As indicated in Section 3, identification of the parameters in the outcome equation requires that the attrition function contains regressors (or instruments) that influence the likelihood of non-response but do not have a direct effect on earnings. We explained earlier that doctors who change postcodes are more likely to drop out; this is not a viable instrument if doctors move by switching into better paying jobs. Instead we use the length of time (in days) that respondents took to return a hardcopy survey or complete an online questionnaire which we showed in Table 3 is negatively associated with the likelihood of dropping out in the next wave, but is not expected to have a direct effect on earnings.

4.2 Estimates of the attrition function

Table 4 shows the estimates from the sequential response probit regressions for GPs and specialists. The estimates are from a 'pooled' model whereby the sequential response function of each wave t is pooled across waves 2 to 4 to maximise statistical power, and estimated using covariates observed at wave *t-1*.

For GPs, the results show a statistically significant relationship between the probability of response with the country of medical training, length of work experience, practice size. All else being equal, GPs that are trained in Australia have a higher probability of responding compared with their overseas trained counterparts. Doctors with more years of experience are also more likely to respond compared with those with less than 10 years since graduating from medical school. GPs from larger practices are also more likely to respond compared with solo practitioners. The length of response time in the preceding survey wave is significantly related to the likelihood of non-response. GPs who took a longer time to respond are more likely to drop out in the next wave. Conditional on the other covariates that influence the likelihood of response, there is no statistically significant relationship between non-response and hours worked.

For medical specialists, those with more years of experience, and those who took a shorter time to return or complete a survey, are more likely to respond in the next wave. The results also indicate that specialists practicing in regional areas are more likely to respond compared with those in major cities. The results also suggest that there are differences in the likelihood of response across different medical specialties.

4.3 Estimates of elasticity on hours

Table 5 and 6 present the estimates on the elasticity on hours worked from the physician earnings equations for GPs and specialists respectively. Columns (1) and (2) show the estimates from the fixed effect estimator ("within estimator") for the unbalanced and balanced samples respectively. Columns (3) and (4) presents the first differences estimators for the unbalanced and balanced samples. Columns (5) and (6) show the estimates from the first differences estimator where attrition is accommodated by the inclusion of the attrition hazard in the earnings equation as described in Section 3. In these models, the attrition hazard is allowed to vary across the different panel waves by interacting the hazard function estimated from the pooled attrition model with a set of wave dummies. The two estimates from the attrition adjusted models differ by whether a constant term is added to the attrition function.

From Table 5, the magnitude of the estimates from the fixed effect and first differences estimators where attrition is not explicitly modelled does not vary significantly, with the fixed effect estimate being slightly larger than the first differences estimate. The estimates from the balanced samples are slightly smaller compared with those from the unbalanced samples. For the attrition adjusted estimates, a test of the null hypothesis that the wave-varying attrition hazard is jointly equal to zero is rejected. This result indicates that the MAR assumption is rejected, suggesting the presence of attrition or selection bias. Although the result suggests the presence of attrition bias, a comparison of the estimates from the first differences estimators with and without attrition adjustment reveals that these estimates are very similar in magnitude. This suggests that despite the presence of attrition bias, attrition in the MABEL survey does not have a significant impact on the estimates of earnings equations for GPs.

The estimates for the earnings model for medical specialists are presented in Table 6. As with the case for GPs, the fixed effect estimates are slightly larger compared with those from the first differences estimators. The estimates from the balanced samples are slightly larger than the unbalanced samples. For the attrition models where the constant is omitted from the attrition function, the null hypothesis that the wave-varying hazard is jointly equal to zero is rejected, suggesting the presence of attrition bias. In the case for specialists, the attrition test is sensitive to the inclusion of a constant term in the attrition function. This is because adding a constant term to the attrition function reduces the size of the coefficients on the attrition hazards. Notwithstanding the difference in the findings on the presence of attrition bias, the estimate of the elasticity on hours is almost identical across the variants of the first differences models. These results suggest, as with the case for GPs, that attrition does not have a significant effect on the estimation of earnings equations for specialists.

4.4 Copula-based estimation

Our copula-based application, as previously stated, requires a parametric assumption about the marginal distribution of the binary attrition variable and the continuous log(earnings) variable. We used the standard probit and logit specifications for the attrition dummy; for log(earnings) we used Gaussian, Student's t (with degrees of freedom left as a free parameter), and logistic alternatives. The main attraction of the Student's t distribution relative to the alternatives is that it can control for excess kurtosis (fat tails) that is a commonly reported feature of earnings.

We have used a suite of Archimedean copulas to combine these margins including the Gaussian, Ali-Mikhail-Haq (AMH), Fairlie-Gumbel-Morgenstern (FGM), Plackett, Gumbel, Clayton, Frank, and Joe copulas; see Trivedi and Zimmer (2007) for additional details. The main differences between these alternative copulas derive from their flexibility in capturing the type of dependence between earnings and attrition. For example, some copulas allow for symmetric positive or negative dependence (e.g. Gaussian) but cannot model tail dependence, whereas others allow only for upper or lower tail dependence (e.g. Gumbel and Clayton). Plackett and Frank copulas have proved popular in empirical work because they are flexible; they model the association between the two margins with a single parameter, and they are comprehensive in that they can model both positive and negative association between the two margins by varying the dependence parameter.

We have no a priori restrictions on the dependence parameter. When, however, any particular specification conflicts with the data, our experience suggests that the maximum likelihood estimation will often fail or estimate a boundary value of the dependence parameter. From among the specifications for which we obtain full estimates, our preferred specification is selected using the Bayesian information criterion.

4.4.1 Copula-based estimation results

For the GP data, using a large number of combinations of margins and copulas, the preferred model(s) is one based on Student t marginal for log(earnings) and probit (or logit) margin for attrition. This is shown in column (7) of Table 5. With these marginal distributions, all alternative copula models generate very similar log-likelihood values close to -4775.2 which is significantly higher than obtained when the Student t is replaced by either normal or logistic margins, combined using any of the previously mentioned copulas.

However, we note that the freely estimated degrees-of-freedom parameter is usually close to 2, a value for which the third and higher moments are undefined. For the selection equation, none of the models indicate evidence in favor of selection bias due to attrition; see the Wald test of independence in Table 5. Not surprisingly, they all deliver similar estimates of the two equations. Note that the results in columns (5) and (6) of Table 5 indicate attrition bias but the key annual-hours elasticity shows quite minor variation. The copula-based estimate of the elasticity is about 0.315, which is lower than the typical estimate obtained under other specifications. However, because the estimates reported in Table 5 are based on samples of different sizes, the conclusion is not clear cut.

For the specialist data, the fits of copulas using the Student t marginal for earnings were no better than those from alternative margins. Moreover, the estimated degrees-of-freedom parameter was typically significantly less than 2, indicating that the variance is undefined. To avoid this problematic outcome, we revert to the results based on logit (for attrition) and logistic (for log earnings) margins. With these margins, Plackett's copula was the best choice and is the basis of the results reported in column (7) of Table 6. The Wald test of independence between attrition and earnings is rejected for p-values less than 0.001. A similar conclusion also implied when the Gaussian copula (which fits less well) is used.

Note that the non copula-based estimates reported in column (5) in Table 6 are also consistent with the finding of attrition bias. The estimated elasticity of earnings with respect to hours is about 0.104, much smaller than for GPs and smaller than the estimates from the conventional selection models. Overall these results favor the hypothesis of attrition-induced selection bias.

We further assess the sensitivity of our results to the length of the panel by leaving out data of the fourth year for the 2008 cohort, and running same analyses on data from

Waves 1 to 3. The coefficient estimates from using the shorter panel are very similar to those discussed above, suggesting that the length of the panel have little bearings on our findings. We also applied inverse probability weighting, and both very similar results for both weighted and unweighted estimates.

5 Top-up samples

Annual top-up samples of doctors are added to the original 2008 cohort of the MABEL survey. From the second and subsequent waves, doctors who are new additions to the AMPCo database, and have not previously been asked to participate, are invited to join the study. These doctors comprise largely of new entrants to the medical workforce, as well as doctors re-entering into active clinical practice in Australia (e.g. returning from overseas, extended leave). The size of new cohorts vary year to year. The number of respondents and response rates for 2009, 2010 and 2011 are 2124 (37.8 percent), 1235 (30.5 percent), and 1219 (38.3 percent) respectively.

Attrition in the top-up samples is considerably higher compared with the 2008 cohort. For instance, as shown in Table 7, 36.2 percent of GPs and 34.3 percent of specialists in the 2009 cohort drop out in the second year. For the 2010 cohort, the attrition rate after the first year is 54.9 percent for GPs and 35.4 for specialists. This is not surprising as the analysis of non-response in the 2008 cohort show that younger doctors are more likely to attrite from the survey.

Table 8 shows the characteristics of the 2008 cohort with the pooled 2009-10 top-up samples by attrition status. Among doctors who responded in every wave of the survey, doctors in the top-up samples have lower mean annual earnings and hours worked, and are more likely to be male, overseas trained, younger, and practise in regional and remote areas. Comparing responders and non-responders in the top-up samples, non-responders have higher mean earnings and hours worked, are less likely to be female, are more likely to be overseas trained and self-employed, and have longer response time in the preceding survey wave.

5.1 Estimates of elasticity on hours: top-up samples

Despite the higher attrition in the top-up samples compared with the 2008 cohort, attrition does not appear to have a significant effect on the estimation of physician earnings equations using the top-up samples. Tables 9 and 10 present the estimated hours elasticities for GPs and specialists for the pooled 2009-10 cohorts. The results show that not only are the hours elasticities in the balanced and unbalanced panels quite similar, these estimates are also not very different compared with those obtained from the attrition model. This is observed even when the attrition models reject the null hypothesis that the wave-varying hazard is jointly equal to zero, suggesting the presence of attrition bias.

5.2 Copula estimation results: top-up samples

The copula-based estimates using the top-up samples data are summarized in Tables 9 and 10. These results are similar to those based on the 2008 cohort data in one respect. They indicate an absence of attrition-based selection bias in the GP sample, and its presence in the specialist sample. Another pattern of results that is also repeated is that the hours elasticity based on the copula specification for specialists is nearly 40 percent smaller than that based on the more conventional selection model.

5.3 Using the top-up samples to handle attrition

By design, the top-up samples in the MABEL survey are new doctors entering into the medical workforce and comprise predominately of younger doctors. We explained earlier that the main purpose of the top-up samples is to maintain the cross-sectional representativeness of the survey. However, although these samples are not strictly “refreshment samples” in the sense of Hirano et al. (2001), they can potentially be used to address panel attrition in the original 2008 cohort. This is because the attritors in the original cohort consist of younger doctors, and by adding the top-up samples to the original cohort one would essentially be replacing the young attritors. Refinements can be made by replacing attritors with top-up doctors identified using propensity score matching (Dorsett 2010).

There are a number of caveats. The inclusion of the young top-up doctors to the 2008 cohort may result in the over-representation of younger doctors. This is potentially a problem if the objective is to compare sample means of different variables, but is not an issue if one is estimating regressions (see Cameron and Trivedi (2005), Chapters 24.2 and 24.3; Solon et al. (2013)).

Secondly, if there is parameter heterogeneity in that the outcomes of interest for the young doctors vary systematically from those of the rest of the population, merging the top-up sample with the attrition-impacted sample may result in a misspecification that would affect the test of the MAR assumption. This can be tested, as we did, by estimating the earnings equation using only the 2008 cohort, using only the top-up samples, and then using the combined pooled sample. The test is performed by calculating the Chow test statistics to test the restriction that the coefficients in the 2008 cohort and the top-up samples are equal. The test statistics are $F(8, 3424) = 5.08$ and $F(8, 3706) = 13.96$ for GPs and specialists respectively, and one can reject the null hypothesis at conventional levels that the earnings regression estimates for the 2008 cohort and the top-up samples are equal.

Finally, the top-up samples become top-up panels when followed over time, and can itself suffer from attrition. It is therefore important that one systematically tests for attrition bias in the original panel, the top-up panels, as well as when these panels are combined.

6 Conclusion

In this paper we assessed the nature and consequences of panel attrition in a unique longitudinal survey of medical doctors. We apply a number of both established and recently developed econometrics methods for modeling attrition bias, as well as the use of top-up samples. Jointly these components provide a comprehensive study of the importance of attrition.

We focus our inquiry on the econometric analysis of physician earnings as a case study of labour market outcomes in the medical sector. Our analysis suggests that the impact of attrition on inference about earnings of GPs is small. This conclusion applies to both the 2008 cohort and the top-up sample of GPs. In the case of specialists the impact is statistically and economically significant, but on the whole is not very large for the variables of interest.

There is an emerging consensus in the literature that attrition does not lead to serious biases in the economic sense, even in the presence of statistical evidence of attrition bias, and large sample attrition (Fitzgerald et al. 1998; Neumark and Kawaguchi 2004; Jones 2007) Based on our results we find that our study is in broad agreement with the general view on the consequences of attrition in panel studies. Our conclusions are but only slightly nuanced for the case of medical specialists, where there appears to be some evidence for an economically significant bias.

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Table 1: Responders and attritors in MABEL - 2008 cohort

Year	Number of doctors	Clinical practice	Non-clinical practice	Total responders	Survival rate (%)	Total attritors	Conditional attrition rate (%)	Cumulative attrition rate (%)	Rejoiners
				— General Practitioners —					
1	3906	3906			100				
2	3066	2954	112	3066	78.5	840	21.5	21.5	
3	2824	2723	101	2824	72.3	1082	12.8	27.7	270
4	2554	2470	84	2554	65.4	1352	13.0	34.6	247
				— Specialists —					
1	4596	4596			100				
2	3670	3491	179	3670	79.9	926	20.2	20.2	
3	3367	3187	180	3367	73.3	1229	12.3	26.7	270
4	3068	2919	149	3068	66.8	1528	12.7	33.2	290

Table 2: Conditional attrition rates by quintiles of annual earnings and hours worked

Year	Annual earnings					Annual hours worked				
	Attrition rate (%), 1^{st} quintile	Attrition rate (%), 2^{nd} quintile	Attrition rate (%), 3^{rd} quintile	Attrition rate (%), 4^{th} quintile	Attrition rate (%), 5^{th} quintile	Attrition rate (%), 1^{st} quintile	Attrition rate (%), 2^{nd} quintile	Attrition rate (%), 3^{rd} quintile	Attrition rate (%), 4^{th} quintile	Attrition rate (%), 5^{th} quintile
— General Practitioners —										
2	17.4	22.3	20.9	21.3	16.8	17.8	21.0	21.6	24.1	19.4
3	14.7	13.8	13.6	15.1	16.4	14.1	15.2	16.9	13.7	16.9
4	14.2	13.0	15.7	17.9	16.4	14.1	12.2	18.9	18.6	18.2
— Specialists —										
2	18.9	16.7	16.8	16.5	19.6	17.8	21.5	18.2	18.1	21.7
3	13.7	12.7	14.7	14.5	13.6	14.1	14.9	14.8	16.0	17.0
4	16.0	10.8	14.6	12.3	14.2	16.4	11.4	15.2	15.0	15.8

Table 3: Attrition rates by earnings quintile and doctors' characteristics

	Earnings quintile: GPs						Earnings quintile: Specialists					
Characteristics	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	All	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	All
Male	19.4	20.8	17.1	19.5	16.2	18.2	16.4	14.4	16.9	14.5	15.7	15.5
Female	14.4	14.8	17.2	16.0	18.3	15.6	16.7	12.5	11.9	15.2	20.0	14.7
Australian medical school												
Yes	15.0	15.8	15.6	16.9	14.8	15.6	15.5	12.6	14.9	14.4	15.9	14.6
No	18.8	21.4	22.0	22.3	21.8	21.4	21.0	18.0	18.4	15.2	16.8	17.7
Experience in years												
< 10	23.8	19.9	23.9	18.4	17.4	21.3	18.8	14.8	13.8	17.0	21.7	17.2
10-19	15.6	14.5	16.6	16.4	20.7	16.5	14.2	15.6	17.7	19.2	16.8	16.8
20-29	9.9	16.4	16.6	19.8	14.9	15.9	18.7	11.4	14.2	13.1	14.3	13.9
30-39	12.7	14.8	12.3	15.9	15.8	14.6	12.5	12.7	18.2	13.3	13.8	14.2
≥ 40	20.6	17.2	18.6	13.9	9.3	16.5	15.3	11.8	8.6	12.8	19.6	13.8
Self-employed												
Yes	20.2	18.9	16.2	18.1	15.2	17.1	15.7	12.7	15.7	16.0	15.4	15.3
No	14.2	15.0	17.3	18.5	19.3	16.3	15.1	14.3	15.4	13.2	14.8	14.5
Ever changed postcode												
Yes	16.6	18.5	20.5	21.4	20.9	19.3	18.2	15.3	14.1	17.1	18.5	16.5
No	13.9	15.2	15.2	17.0	15.7	15.4	15.0	13.7	15.5	14.0	15.4	14.5
Response time quartile												
1^{st}	12.9	14.1	14.8	17.5	13.3	14.5	14.5	10.4	13.2	12.2	13.4	12.7
2^{nd}	14.6	16.4	16.9	15.5	17.3	16.1	14.6	11.0	13.3	13.4	15.8	13.6
3^{rd}	20.9	18.6	18.3	21.2	19.4	19.7	17.5	18.3	19.1	14.8	18.3	17.6
4^{th}	17.1	23.8	24.5	21.9	21.6	21.5	22.4	19.5	21.1	23.1	19.7	21.2

Table 4: Estimates from pooled sequential response regressions for General Practitioners and specialists

	General Practitioners		Specialists	
	Coeff.	Std Err.	Coeff.	Std Err.
Log(Annual Hours)	-0.06	0.05	-0.04	0.05
Female	0.07	0.05	0.03	0.05
Temporary visa	0.14	0.14	-0.29	0.20
Australian medical school	0.18***	0.05	0.06	0.05
Fellow	0.07	0.04	0.15	0.10
Number of postgraduate qual.	0.04	0.03	0.02	0.04
Do hospital work	-0.05	0.05		
Percentage clinical work			0.0001	0.001
Self-employed	0.002	0.002	-0.07*	0.04
Experience (*Excl: < 10 years*)				
10-19 years	0.30***	0.07	0.06	0.06
20-29 years	0.32***	0.07	0.17***	0.06
30-39 years	0.38***	0.08	0.18***	0.06
≥40 years	0.29***	0.10	0.22***	0.08
Practice size (*Excl: Solo*)				
2-3 doctors	0.24***	0.08		
4-5 doctors	0.21***	0.08		
6-9 doctors	0.17**	0.07		
≥10 doctors	0.18**	0.08		
Specialty (*Excl: Paediatrics*)				
Cardiology			-0.06	0.16
Gastroenterology			-0.03	0.15
General medicine			0.05	0.14
Intensive care			-0.03	0.18
Thoracic medicine			-0.13	0.15
Int. med.: Other			-0.01	0.09
Pathology			-0.07	0.13
General surgery			-0.14	0.12
Orthopaedic surgery			-0.004	0.13
Surgery: Other			-0.09	0.11
Anaesthesia			0.08	0.09
Diagnostic radiology			-0.29**	0.12
Emergency medicine			-0.03	0.11
Obstetrics/Gynaecology			-0.08	0.11
Ophthalmology			-0.17	0.13
Psychiatry			-0.09	0.10
Other			-0.15	0.11
State (*Excl: New South Wales*)				
Victoria	-0.07	0.05	0.01	0.05
Queensland	-0.09	0.06	-0.06	0.06
South Australia	0.15*	0.08	-0.11	0.13
Western Australia	-0.11	0.07	-0.10	0.05
Tasmania	-0.07	0.12	-0.05	0.06
Australian Capital Territory	-0.27*	0.16	0.15	0.16
Northern Territory	0.03	0.16	-0.28	0.24
Remoteness (*Excl: Major city*)				
Inner regional	0.03	0.06	0.11*	0.06
Other	0.03	0.07	0.22*	0.13
Time to response	-3.55***	0.54	-2.15***	0.83

Continued on next page

Table 4 – continued from previous page

	General Practitioners		Specialists	
	Coeff	Std Err	Coeff	Std Err
Time to response^2	2.72***	0.42	1.53***	0.62
Constant	0.22	0.44	0.26	0.64
Number of observations	5166		2139	

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

Table 5: Earnings model for General Practitioners - 2008 cohort

	(1) Unbalanced: Fixed effects	(2) Balanced: Fixed effects	(3) Unbalanced: First differences	(4) Balanced: First differences	(5) Attrition adjusted: no constant	(6) Attrition adjusted: with constant	(7) Copula selection model
Coefficient on hours	0.460	0.407	0.428	0.387	0.422	0.418	0.315
	(0.027)	(0.038)	(0.042)	(0.055)	(0.041)	(0.041)	(0.043)
Wave-varying attrition hazards:							
Wald test of joint significance (χ^2)					42.47	29.16	
Wald test: p-value					0.000	0.000	
Degrees of freedom					3	3	
Dependence in copula model:							
Wald test of independence							1.862
Wald test: p-value							0.172
Number of observations	7776	3464	4106	2598	4043	4043	5166

Note: Robust-clustered standard errors used in columns (3) and (4). Bootstrapped standard errors in columns (5) and (6). The total number of covariates is 25. Additional covariates include visa status, hospital work, self-employment, experience, practice size, states/territory and remoteness. In column (7), the preferred copula selection model is based on Student t marginal for logarithm of earnings, probit marginal for attrition, and the Frank copula.

Table 6: Earnings model for specialists - 2008 cohort

	(1) Unbalanced: Fixed effects	(2) Balanced: Fixed effects	(3) Unbalanced: First differences	(4) Balanced: First differences	(5) Attrition adjusted: no constant	(6) Attrition adjusted: with constant	(7) Copula selection model
Coefficient on hours	0.287	0.356	0.174	0.244	0.180	0.181	0.104
	(0.022)	(0.029)	(0.038)	(0.053)	(0.035)	(0.035)	0.026
Wave-varying attrition hazards:							
Wald test of joint significance (χ^2)					38.65	2.93	
Wald test: p-value					0.000	0.403	
Degrees of freedom					3	3	
Dependence in copula model:							
Wald test of independence							7535.119
Wald test: p-value							0.000
Number of observations	8904	4204	4921	3153	4875	4875	6109

Note: Robust-clustered standard errors used in columns (3) and (4). Bootstrapped standard errors in columns (5) and (6). The total number of covariates is 29. Additional covariates include visa status, percentage of time in clinical practice, experience, self-employment, specialty, states/territory and remoteness. In column (7), the preferred copula selection model is based on the logistic marginal for log earnings, logit marginal for attrition, and the Plackett copula.

Table 7: Responders and attritors in MABEL - 2009 and 2010 cohorts

Year (Cohort)	Number of doctors	Clinical practice	Non-clinical practice	Total responders	Survival rate (%)	Total attritors	Conditional attrition rate (%)	Cumulative attrition rate (%)	Rejoiners
—— General Practitioners ——									
(2009 cohort)									
1	543	543			100				
2	343	334	9	343	63.2	200	36.2	36.2	
3	302	283	19	302	55.6	241	16.2	44.4	57
(2010 cohort)									
1	448	448			100				
2	243	225	18	243	45.1	205	54.9	54.9	
—— Specialists ——									
(2009 cohort)									
1	484	484			100				
2	318	305	13	318	65.7	166	34.3	34.3	
3	303	295	8	303	62.6	181	12.8	37.4	50
(2010 cohort)									
1	370	370			100				
2	239	230	9	239	64.6	131	35.4	35.4	

Table 8: Characteristics of 2008 cohort and 2009-2010 top-up samples by attrition status

	General Practitioners				Specialists			
	Always in		Always out		Always in		Always out	
	2008	2009-10	2008	2009-10	2008	2009-10	2008	2009-10
Mean annual earnings ('000)	172.4	143.3*	176.6	168.1†	337.5	245.6*	340.9	236.0
Mean Annual hours	2016	1923.5*	2106.4	2048.4†	2316.4	2156.0*	2337.7	2265.2†
Female (%)	48.5	61.5*	49.1	45.7†	29.0	42.5*	25.5	37.1
Temporary visa (%)	2.1	19.3*	3.2	24.5	0.7	5.7*	1.3	9.8†
Australian medical school	82.3	46.9*	73.9	34.9†	83.2	58.1*	80.8	50.2
Fellow (%)	57.4	35.4*	55.4	34.2	96.6	60.5*	94.8	64.4
Num. postgrad qualification	0.6	0.3*	0.5	0.3	0.2	0.2*	22.5	0.1†
Do hospital work (%)	24.3	24.8	26.8	23.0	-	-	-	-
% time in clinical practice	-	-	-	-	78.0	75.7*	79.2	75.7
Self-employed (%)	44.6	10.2*	46.2	14.7†	43.5	17.8*	45.5	19.0
Experience in years (%)								
<10	10.8	41.1*	14.9	39.6	14.7	56.6*	16.5	58.5
10-19	23.1	33.9*	22.7	34.2	15.8	18.7	18.5	15.6
20-29	36.2	15.1*	34.0	15.8	35.8	17.8*	32.9	22.4
30-39	23.7	6.5*	20.7	7.6	24.3	5.4*	22.2	2.4†
≥40	6.1	3.4*	7.6	2.9	9.4	1.5*	9.9	1.0
Major city (%)	64.7	55.5*	64.2	49.3	83.1	80.7	85.8	77.6
Inner regional (%)	21.2	24.0	20.5	29.1	13.4	13.9	11.8	19.5†
Outer regional, remote (%)	14.1	20.6*	15.4	21.6	3.5	5.4*	3.4	2.9
Time to response (days)	29.8	91.9*	35.6	128.7†	35.6	90.5	41.5	125.2†
Number of observations	1698	384	1119	278	1896	332	1143	205

*Significantly different from 2008 cohort at 10%. †Significantly different from 2009-10 "Always-in" at 10%.

Table 9: Earnings model of General Practitioners - 2009-2010 cohorts

	(1) Unbalanced: Fixed effects	(2) Balanced: Fixed effects	(3) Unbalanced: First differences	(4) Balanced: First differences	(5) Attrition adjusted: no constant	(6) Attrition adjusted: with constant	(7) Copula selection model
Coefficient on hours	0.618	0.669	0.613	0.636	0.576	0.591	0.448
	(0.095)	(0.115)	(0.141)	(0.174)	(0.129)	(0.126)	(0.112)
Wave-varying attrition hazards:							
Wald test of joint significance					19.81	2.23	
Wald test: p-value					0.000	0.328	
Degrees of freedom					3	3	
Dependence in copula model:							
Wald test of independence							0.154
Wald test: p-value							0.694
Number of observations	1190	577	435	342	526	526	883

Note: Robust-clustered standard errors used in columns (3) and (4). Bootstrapped standard errors in columns (5) and (6). The total number of covariates is 15, and is less than the set of covariates for the 2008 cohort due to the smaller size of the top-up samples. Additional covariates include visa status, hospital work, self-employment, experience, states/territory and remoteness. In column (7), the preferred copula selection model is based on Student t marginal for log earnings, logit marginal for attrition, and the Plackett copula.

Table 10: Earnings model of Specialists - 2009-2010 cohorts

	(1) Unbalanced: Fixed effects	(2) Balanced: Fixed effects	(3) Unbalanced: First differences	(4) Balanced: First differences	(5) Attrition adjusted: no constant	(6) Attrition adjusted: with constant	(7) Copula selection model
Coefficient on hours	0.773	0.870	0.654	0.741	0.669	0.646	0.375
	(0.065)	(0.069)	(0.165)	(0.181)	(0.144)	(0.149)	(0.161)
Wave-varying attrition hazards:							
Wald test of joint significance (χ^2)					51.24	5.39	
Wald test: p-value					0.000	0.067	
Degrees of freedom					3	3	
Dependence in copula model:							
Wald test of independence							10.322
Wald test: p-value							0.000
Number of observations	1017	520	402	312	456	456	709

Note: Robust-clustered standard errors used in columns (3) and (4). Bootstrapped standard errors in columns (5) and (6). The total number of covariates is 8, and is less than the set of covariates for the 2008 cohort due to the smaller size of the top-up samples. Additional covariates include visa status, experience, self-employment, broad specialty groups, states/territory and remoteness. In column (7), the preferred copula selection model is based on logistic marginal for log earnings, logit marginal for attrition, and the Gumbel copula.

A Appendix

Table A.1: Baseline cohort characteristics in 2008 by attrition status

	General Practitioners			Specialists		
	Always in	Always out	Rejoin	Always in	Always out	Rejoin
Mean annual earnings ('000)	172.4	177.5	174.4	337.5	341.4	339.6
Quartiles ('000)						
q25	91.0	100.0	96.0	190.0	180.0	181.2
q50	147.2	150.0	150.0	274.7	280.0	270.0
q75	220.0	240.0	230.7	400.0	400.0	400.0
Mean Annual hours	2011.4	2121.8***	2070.6	2316.4	2349.5	2309.1
Quartiles						
q25	1456.0	1664.0	1560.0	1976.0	1976.0	1950.0
q50	2080.0	2132.0	2080.0	2340.0	2340.0	2340.0
q75	2548.0	2600.0	2600.0	2756.0	2860.0	2750.0
Female (%)	48.5	42.9***	42.9*	29.0	25.2**	33.5
Temporary visa (%)	2.1	4.1***	1.1	0.7	1.5**	0.9
Australian medical school	82.3	72.5***	77.1**	83.2	80.7	80.8
Fellow (%)	57.4	54.5**	57.4	96.6	94.7**	95.2
Num. postgrad qualification	0.6	0.5***	0.5*	0.2	0.2	0.2
Do hospital work (%)	24.3	27.8*	24.4	-	-	-
% time in clinical practice	-	-	-	78.0	80.1**	77.0
Self-employed (%)	44.6	44.8	49.4	43.5	47.2*	41.4
Experience in years (%)[a]						
<10	10.8	14.3**	16.4***	14.7	13.6	23.7***
10-19	23.1	21.2	26.2	15.8	18.5*	18.3
20-29	36.2	34.4	33.0	35.8	34.8	28.2***
30-39	23.7	22.5	16.7***	24.3	23.2	19.8**
≥ 40	6.1	7.5	7.7	9.4	9.9	9.9
Major city (%)	64.7	65.8	60.4	83.1	83.3	88.3**
Inner regional (%)	21.2	19.3	23.2	13.4	13.1	8.7**
Outer regional, remote (%)	14.1	14.9	16.4	3.5	3.5	3.0
Time to response (days)	29.8	35.6***	35.7***	35.6	40.0***	45.2***
Number of observations	1698	783	336	1896	810	333

Note: Significantly different from "Always in": *** 1%, ** 5%, * 10%.

[a] For specialists, the first two experience categories are < 15 years, and 15-19 years.