A Predicting wages for those who are not employed

The conventional Heckman approach is used to predict wages for those who are not employed in order to include wages as an explanatory variable in the structural dynamic labour supply model. The approach involves three steps, as can be seen from a brief description of the model. Formally, let the wage equation for a person *i*, randomly picked up from the working-age population, be

$$\ln(w_i) = x_i'\beta + \omega_i, \tag{A.1}$$

where $ln(w_i)$ refers to the natural log of wages of individual *i*; x_i is a vector of wage covariates associated with individual *i*; ω_i is an error term with zero mean and variance δ_ω^2 . The error term ω_i summarizes all unobserved determinants of wages for individual *i*.

However, since wages are not observed for those who are not employed, equation (A.1) cannot be estimated using a sample that comprises both those who are employed and those who are not employed. On the other hand, the parameters β in equation (A.1) will be estimated with bias if the equation is estimated only on those who are employed, since unobserved determinants of wages (ω) are likely to be systematically different between those who are employed and those who are not employed (Greene 2000). In other words, ω_i is likely to be correlated with the unobserved determinants of employment status of person *i*. Let the determination of employment status of individual *i* be described as

$$E_i^* = z_i'\varphi + \psi_i, \text{ with } E_i = \begin{cases} = 1 & (employed) \quad if\ E_i^* > 0 \\ = 0 & (not\ employed) \quad f\ E_i^* \le 0 \end{cases}, \tag{A.2}$$

Where E_i^* denotes the propensity of employment of individual *i*; E_i refers to observed employment status. z_i is a vector of observed variables that affect individual employment status; ψ_i is an error term, summarising unobserved determinants of employment status. If ω_i and ψ_i are correlated with a correlation coefficient ρ, and ψ_i is assumed to follow the normal distribution with mean zero

and normalised variance of unity, then it can be shown that for those who are employed, their expected log-wage can be written as (Greene 2000):

$$\ln(w \mid E=1) = x'\beta + \rho\delta_{\omega} \cdot \lambda_1, \text{ with } \lambda_1 = \frac{\phi(z'\varphi)}{\Phi(z'\varphi)}; \tag{A.3}$$

And for those who are not employed, their expected log-wage can be written as

$$\ln(w \mid E=0) = x'\beta + \rho\delta_{\omega} \cdot \lambda_0, \text{ with } \lambda_0 = -\frac{\phi(z'\varphi)}{1-\Phi(z'\varphi)}, \tag{A.4}$$

where $\phi(.)$ refers to the standard normal density function, and $\Phi(.)$ the standard normal cumulative probability function.

Therefore, the first step for predicting wages is to estimate the employment status equation (A.2), and then to use the resulting parameters $\hat{\varphi}$ to compute $\hat{\lambda}_1$, known as the inverse Mills' ratio, for those who are employed, and $\hat{\lambda}_0$ for those who are not employed. In the second step, the wage equation (A.3) is estimated for those who are employed. Note that in the second step $\hat{\lambda}_1$ is included in the wage equation as one of the explanatory variables.[1] In the third step, wages for those who are not employed are predicted using equation (A.4) with the parameter estimates from the second step and $\hat{\lambda}_0$ from the first step.

Predicted wages for women and their partner were done separately. The employment and wage equations for women are reported in table A.1, the corresponding wage and employment status models for the partner are presented in table A.2. Note that for identification purposes, in the employment status equation estimated using a Probit model, the variables for the number and age of young children and non-labour income are included. These variables are excluded from the wage equation.

[1] Note that $\rho\delta_{\omega}$ is estimated as one coefficient parameter on $\hat{\lambda}_1$ in the second step. But if one wishes, ρ and δ_{ω} can be calculated using the formulas described in Greene (2000).

Table A.1 **Employment and wage equation for predicting wages — Women**

	Wage equation		*Employment equation*	
	Coef.	*S.E.*	*Coef.*	*S.E.*
Degree	0.5181	0.0293	0.9348	0.0442
Diploma	0.2539	0.0296	0.5459	0.0533
Certificate	0.0698	0.0266	0.3601	0.0484
Year 12	0.1500	0.0265	0.4059	0.0467
Tenure	0.0130	0.0029		
Tenure squared	-0.0003	0.0001		
Work experience	0.0323	0.0055	0.1227	0.0061
Work experience square	-0.0006	0.0001	-0.0020	0.0002
NESC	0.0069	0.0255	-0.1726	0.0515
ESC	-0.1129	0.0255	-0.2720	0.0482
Health	-0.1728	0.0264	-0.5735	0.0388
VIC	-0.0227	0.0204	-0.0942	0.0418
QLD	-0.0394	0.0221	-0.1081	0.0445
SA	-0.1043	0.0279	-0.1018	0.0567
WA/NT	-0.0934	0.0286	-0.2087	0.0536
TAS	0.0500	0.0460	-0.0197	0.0969
Capital city	0.1290	0.0167	-0.1501	0.0334
Wave 2	-0.0242	0.0263	-0.0702	0.0530
Wave 3	-0.0510	0.0266	-0.1127	0.0528
Wave 4	-0.0416	0.0265	-0.1111	0.0530
Wave 5	-0.0166	0.0264	-0.0885	0.0535
Wave 6	0.0216	0.0265	-0.1111	0.0537
Child 0-2			-0.4531	0.0351
Child 3-5			-0.1776	0.0353
Child 6-17			0.0800	0.0153
Non-labour income ($10000)			-0.0145	0.0025
Lambda (λ_1)	0.3185	0.0633		
Constant	2.0269	0.0854	-0.6001	0.0748

Table A.2 **Employment and wage equation for predicting wages — Men**

	Wage equation		*Employment equation*	
	Coef.	*S.E.*	*Coef.*	*S.E.*
Degree	0.4456	0.0338	0.7285	0.0639
Diploma	0.2719	0.0337	0.3323	0.0730
Certificate	0.0155	0.0273	0.3782	0.0511
Year 12	0.1286	0.0395	0.6849	0.0896
Tenure	0.0033	0.0026		
Tenure squared	-0.0002	0.0001		
Work experience	0.0111	0.0048	0.0581	0.0091
Work experience square	-0.0002	0.0001	-0.0011	0.0002
NESC	-0.0717	0.0246	0.0512	0.0660
ESC	-0.1778	0.0343	-0.6309	0.0613
Health	-0.0545	0.0580	-1.1600	0.0422
VIC	-0.0308	0.0215	0.0109	0.0569
QLD	-0.0209	0.0234	-0.0602	0.0591
SA	-0.2467	0.0295	-0.0390	0.0744
WA/NT	-0.0906	0.0285	0.0580	0.0762
TAS	0.0883	0.0519	-0.2030	0.1094
Capital city	0.2658	0.0177	0.0738	0.0452
Wave 2	-0.0239	0.0276	-0.0662	0.0726
Wave 3	-0.0314	0.0276	0.0558	0.0734
Wave 4	-0.0060	0.0276	-0.0090	0.0725
Wave 5	0.0219	0.0278	-0.0449	0.0716
Wave 6	0.0388	0.0283	-0.1352	0.0708
Child 0-2			0.1123	0.0562
Child 3-5			0.1704	0.0589
Child 6-17			0.1428	0.0231
Non-labour income ($10000)			-0.0052	0.0041
Lambda (λ_1)	-0.1153	0.1475		
Constant	2.4909	0.0773	0.6329	0.1322