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FIML estimation of an endogenous switching model for count data

Alfonso Miranda
Economics Department
University of Warwick

Abstract. This paper presents code for fitting a FIML endogenous switching Poisson count model for cross-sectional data in Stata 7: the `espoisson` command. The Poisson process depends on an unobserved heterogeneity term, ξ; a set of explanatory variables, x; and an endogenous dummy, d. The endogenous dummy depends on an unobserved random term, ν. Correlation between ξ and ν is allowed. If a model with exogenous d is fitted instead, correlation between ξ and ν will result in simultaneous equation bias. The endogenous switching model corrects this problem. After describing the underlying econometric theory behind the command, an example is discussed.

Keywords: st0057, count models, endogenous switch, sample selection

1 Introduction

In recent years, count data models have become one of the most important tools available to statisticians and econometricians. Among other application fields, count models are valuable in the study of work-related training (Arulampalam and Booth 1997), recreation demand (Terza 1998), cigarette consumption (Yen 1999; Mullahy 1997), accidents (Feinstein 1989; Minchener and Tighe 1992; Lee, Stevenson, and Wong 2002), embryonic development (Egel and Brake 1993), health care demand (Windmeijer and Santos 1997; Gurmu 1997; Cameron and Windmeijer 1996), clinical research (Kianifard and Gallo 1995; Cook and Wei 2002), innovation and technology adoption (Faria, Fenn, and Bruce 2003; Hausman, Hall, and Griliches 1993), labor mobility (Winkelmann 1996, 2001), airline safety (Evans 1989), and fertility behavior (Kalwij 2000; Melkersson and Rooth 2002; Wang and Famoye 1997; Santos and Covas 2000).

A common situation found in applied work is that of sample selection and endogenous dummy explanatory variables. These features pose important empirical challenges, as failure to control for them generally leads to biased and inconsistent estimators if unobserved individual heterogeneity is present (Heckman 1979; Mullahy 1997). Under such circumstances, three strategies for consistent estimation have been proposed. One strategy considers a two-step method of moments (TSM) estimator that is in the spirit of Heckman's sample selection model (Heckman 1979; Terza 1998; Greene 1994, 1997). Sample selection models of the kind discussed by Heckman (1979) can be fitted using Stata's `heckman` command; see [R] **heckman**. A second alternative consists of a nonlinear weighted least-squares estimator (Terza 1998). Finally, Terza (1998) outlines a full information maximum likelihood (FIML) procedure. FIML and nonlinear

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weighted least squares (NWLS) are statistically efficient but computationally expensive compared with TSM. NWLS is computer efficient relative to FIML and statistically efficient relative to TSM. Hence, FIML delivers the statistically most-efficient estimator if the researcher is comfortable imposing some distributional assumptions. The fact that FIML places heavy demand on computer power has discouraged its use in applied work (Terza 1998). However, recent applications suggest that the computational costs of FIML are fairly affordable with modern computers (Greene 1997).

The objective of this paper is to present an econometric module for fitting a FIML endogenous switching Poisson count model implemented in Stata 7. The remainder of the present work unfolds as follows. In section two, the underlying econometric theory behind the `espoisson` command is discussed. Section three introduces the syntax for `espoisson`. Section four presents an empirical application, and finally, section five includes some concluding comments.

2 The model

This section follows the discussion in Terza (1998). Consider the ith individual from a random sample $I = \{1 \ldots n\}$. Conditional on a vector of explanatory variables x_i, an endogenous dummy d_i, and a random term ξ_i, the dependent variable y_i—which is a count—is supposed to follow a standard Poisson distribution,

$$f(y_i|\xi_i) = \frac{\exp\left\{-\exp\left(x_i'\beta + \gamma d_i + \xi_i\right)\right\}\left\{\exp\left(x_i'\beta + \gamma d_i + \xi_i\right)\right\}^{y_i}}{y_i!} \tag{1}$$

The random term ξ_i is commonly interpreted as a variable that summarizes omitted and unobserved variables. In some contexts, ξ_i can be also interpreted as a measurement error. Given a vector of explanatory variables z_i (which may contain some or all elements of x_i), d_i is characterized by an index process

$$d_i = \begin{cases} 1 & \text{if } z_i'\alpha + \nu_i > 0 \\ 0 & \text{otherwise} \end{cases}$$

Let w_i represent all exogenous variables, and suppose that ξ_i and ν_i are jointly normal with mean zero and covariance matrix

$$\Sigma = \begin{pmatrix} \sigma^2 & \sigma\rho \\ \sigma\rho & 1 \end{pmatrix}$$

Conditional on ξ_i, d_i and y_i are independent. Hence, the joint conditional probability density function of y_i and d_i, given w_i, can be written as

$$\begin{aligned} f\left(y_i, d_i|w_i\right) \quad = \quad & \int_{-\infty}^{\infty} \Big\{ d_i f\left(y_i|d_i = 1, w_i, \xi_i\right) \Pr\left(d_i = 1|w_i, \xi_i\right) \\ & + \left(1 - d_i\right) f\left(y_i|d_i = 0, w_i, \xi_i\right) \Pr\left(d_i = 0|w_i, \xi_i\right) \Big\} f\left(\xi i\right) d\xi_i \end{aligned}$$

where $f(\xi_i)$ denotes the probability density function for the random term ξ_i. Consider now a change of variable

$$\eta_i = \frac{\xi_i}{\sigma\sqrt{2}}$$

Exploiting the fact that $f(\xi_i|w_i)$ is normal with mean zero and variance σ^2, the joint conditional probability density function of y_i and d_i, given w_i, may be re-expressed as

$$\begin{aligned} f\left(y_i, d_i|w_i\right) &= \frac{1}{\sqrt{\pi}}\int_{-\infty}^{\infty}\left[f\left(y_i|d_i, w_i, \sigma\eta_i\sqrt{2}\right)\left\{d_i\Phi_i^*\left(\sigma\eta_i\sqrt{2}\right)\right.\right. \\ &\quad \left.\left. + \left(1-d_i\right)\Phi_i^*\left(-\sigma\eta_i\sqrt{2}\right)\right\}\right]\exp\left(-\eta_i^2\right)d\eta_i \end{aligned} \tag{2}$$

where

$$\Phi_i^*\left(\sigma\eta_i\sqrt{2}\right) = \Phi\left(\frac{z_i'\alpha + \rho\eta_i\sqrt{2}}{\sqrt{1-\rho^2}}\right)$$

The integral in (2) does not admit a closed-form solution. However, Gauss–Hermite quadrature can be used to approximate it. Having defined (2) the log likelihood is simply

$$\text{Log}L = \sum_{i=1}^{n}\ln\left\{f\left(y_i, d_i|w_i\right)\right\}$$

The model is identified through functional form. Hence, vectors x_i and z_i may contain the same elements (i.e., no exclusion restrictions are required to secure identification). Unlike the Tobit model, [R] **tobit**, coefficients on common elements of x_i and z_i may have different signs in β and α (for more details on the Tobit model, see Greene 2003, chapter 22). Notice that the mean and variance of the count variable are

$$\begin{aligned} \mu_i &= E\left[y_i|d_i, w_i\right] \\ &= \exp\left\{x_i'\beta - 0.5\sigma\right\}\left[d_i\left\{\frac{\Phi\left(z_i'\alpha+\sigma\rho\right)}{\Phi\left(z_i'\alpha\right)}\right\}\right. \\ &\quad \left. + \left(1-d_i\right)\left\{\frac{1-\Phi\left(z_i'\alpha+\sigma\rho\right)}{1-\Phi\left(z_i'\alpha\right)}\right\}\right] \end{aligned}$$

and

$$\text{Var}\left(y_i|d_i, w_i\right) = \mu_i + k\mu_i^2$$

$k = \exp\left(2\sigma^2\right) - \exp\left(\sigma^2\right)$. Thus, the model exhibits overdispersion as σ is by definition positive. The log-likelihood function is maximized using the Newton–Raphson algorithm. If H represents the Hessian matrix at convergence, $-H^{-1}$ provides an estimator for the covariance matrix. Usual hypothesis tests are valid on the basis of LR and Wald statistics.

If $\rho = 0$, ξ_i and ν_i are independent. In such a case, d_i can be treated as an exogenous variable in (1) without risk of inducing simultaneous equation bias. Besides, if $\rho = 0$, the switch between regimes (i.e., the change from $d_i = 0$ to $d_i = 1$) becomes an exogenous process. Hence, a test for the adequacy of the endogenous switching model can be performed on the basis of a likelihood-ratio test for the significance of ρ. Notice, however, that under the null hypothesis ρ lies on the boundary of the set of its admissible values. Thus, the likelihood-ratio statistic is distributed as a 50:50 mixture of a mass point at zero and a chi-squared variable with one degree of freedom (Self and Liang 1987; Gutierrez, Carter, and Drukker 2001).

3 Syntax

`espoisson` *depvar* [*varlist*] [`if` *exp*] [`in` *range*] , `edummy(`*varname*`)`
[`switch(`*varlist*`)` `quadrature(`#`)` `rho0(`#`)` `sigma0(`#`)` `exs` *maximize_options*]

The syntax follows the standard form for estimation commands in Stata. *depvar* represents the dependent count variable, and *varlist* specifies covariates for the Poisson process (the *varlist* should include the endogenous dummy variable as one of its elements). Then, the endogenous dummy variable should be declared by means of the required option `edummy()`. The `switch()` option specifies covariates for the switching variable, and `quadrature()` indicates the number of quadrature points used in the numerical approximation of the integral in (5). Option `exs` causes Stata to fit the model under the restriction $\rho = 0$. This last specification corresponds to an exogenous switching model, EXS. Finally, options `rho0()` and `sigma0()` set initial values for ρ and σ, respectively. The command `espoisson` is written in terms of an `ml d0` method; however, an `ml lf` method is feasible. The syntax of `predict`, [R] **predict**, after `espoisson` is

`predict` *newvarname* [`if` *exp*] [`in` *range*] , `n`

Option `n` for `predict` gives Stata instructions to calculate the predicted mean number of events; see [R] **poisson**. This is the only option available.

4 Illustration: Completed fertility and primary education in Mexico

To illustrate the methodology, some regressions for completed fertility in Mexico are performed. Data from the National Survey of Demographic Dynamics 1997 (ENADID from its acronym in Spanish) is used. The ENADID is a micro-dataset containing detailed economic and demographic information for 88,022 Mexican women aged between 15 and 54 years. Since completed fertility is the main concern, a total of 19,559 cases of women aged 40 or over at the time of the survey (December 1997) were selected. The dependent variable, `children`, represents the total number of live births experienced by women during their fertile period of life, including children that died a few hours after birth. The mean of the dependent variable is 4.5, and its standard deviation is 2.77. Hence, unconditional variance (7.67) is larger than unconditional mean, suggesting that the data is overdispersed. The following explanatory variables are considered in the Poisson process:

- `edu12`. Dummy variable taking the value of one if the index woman completed primary education and zero otherwise.
- `catholic`. Dummy variable indicating if the individual is Catholic (`catholic`= 1).
- `indspker`. Dummy variable indicating whether the index woman can speak an indigenous language. This is a proxy variable for ethnic group.
- `after49`. Dummy variable taking the value of one if the index woman was born after 1949 and zero otherwise. This variable is intended to capture potential generation effects.

As religious teaching is banned in the Mexican public education system, it is unlikely that either Catholics or non-Catholics would systematically avoid primary school because of their religious beliefs. Hence, an exclusion restriction for the switch process is suggested, namely, that religion does not affect a woman's likelihood of graduation from primary school. This exclusion restriction is suggested in the context of Mexico and, as discussed in section 2, it is not technically required to secure identification.

`children` has a mode of three, representing approximately 17% of the sample. Around six percent of women report zero counts, and fewer than three percent had more than ten live births. Finally, women with one and two children contribute 6% and 13% of all cases, respectively. Comparing these last two figures with the proportion of one and two counts that a standard Poisson distribution would predict (5.8% and 11.8% respectively), it is possible to say that there is no excess of such counts. Hence, relative to data from developed countries, Mexican women appear neither to have special predilection for the two-child family nor to avoid having only one child (see the discussion in Santos and Covas 2000). In the case of zero counts, things are different. According to a standard Poisson distribution, childless women should represent 1.3% of the sample, far below the actual figure of 6% contained in the ENADID. Thus, zero-inflated count models seem to be justified. Fitting zero-inflated models, however, is beyond the scope of the present paper, as this section deals only with an illustration of the FIML endogenous switching procedure. Descriptive statistics are obtained using the `summarize` command.

```
. use espoisson.dta
(Mexico Completed Fertility Data)
. summarize
```

Variable	Obs	Mean	Std. Dev.	Min	Max
age	19559	45.93481	4.210048	40	54
children	19559	4.428652	2.753055	0	18
catholic	19559	.8943709	.3073702	0	1
indspker	19559	.0940232	.2918685	0	1
after49	19559	.6184365	.4857827	0	1
edu12	19559	.5064676	.4999709	0	1

Economic theory suggests that parents' education increases the opportunity cost of children (Willis 1973). Consequently, `edu12` is expected to have a negative effect on completed fertility. Similarly, intuition suggests that `after49` should have a negative coefficient in the Poisson process and a positive coefficient in the switch equation as per-period fertility rates in Mexico have dropped consistently in the last 30 years and average education has increased from 3.4 to 7.6 years (INEGI 2001). `indspker` is expected to have a positive coefficient in the Poisson process and a negative coefficient in the switch, given that indigenous people in general have limited access to education and health services in Mexico. Finally, `catholic` might have a coefficient of either sign.

For comparison purposes, a model with exogenous switching (EXS) is reported along with results for the endogenous switching model (ENS). The EXS model is obtained as an ENS model in which the restriction $\rho = 0$ has been imposed. Thus, EXS is nested within ENS. In all estimated regressions, allowing for more than sixteen quadrature points did not result in either significant improvement of the log likelihood or significant modifications of the parameters. Therefore, models with sixteen quadrature points are reported. The exogenous switching model (EXS) is fitted using the `exs` option:

```
. espoisson children catholic indspker after49 edu12, ed(edu12) s(indspker after49)
> q(16) exs difficult
Getting Initial Values:
Fitting Full model:
Iteration 0:   log likelihood = -62984.076
Iteration 1:   log likelihood = -62835.643  (not concave)
Iteration 2:   log likelihood = -57996.399
Iteration 3:   log likelihood = -57750.848
Iteration 4:   log likelihood = -57633.216
Iteration 5:   log likelihood = -57633.143
Iteration 6:   log likelihood = -57633.143

Exogenous-Switch Poisson Regression
(16 quadrature points)
                                                  Number of obs   =      19559
                                                  Wald chi2(4)    =    4067.23
Log likelihood = -57633.143                       Prob > chi2     =     0.0000
```

children	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
children						
catholic	-.037471	.0129797	-2.89	0.004	-.0629108	-.0120312
indspker	.0259196	.0134347	1.93	0.054	-.0004119	.052251
after49	-.1498285	.0082753	-18.11	0.000	-.1660478	-.1336093
edu12	-.4819543	.0084677	-56.92	0.000	-.4985507	-.4653579
_cons	1.778055	.0137364	129.44	0.000	1.751132	1.804978
switch						
indspker	-1.127517	.0368167	-30.63	0.000	-1.199676	-1.055358
after49	.2931059	.0188494	15.55	0.000	.2561617	.3300501
_cons	-.0731283	.0149867	-4.88	0.000	-.1025016	-.0437549
sigma	.2965293	.0054761	54.15	0.000	.2859882	.307459

According to these results, σ is positive and significantly different from zero. Therefore, there is evidence that overdispersion and unobserved heterogeneity are present. All estimated coefficients are significant and have the expected sign—though `indspker` in the Poisson process is significant only at 10% of confidence. Removing the `exs` option causes Stata to fit the endogenous switching model (ES):

```
. espoisson children catholic indspker after49 edu12, ed(edu12) s(indspker after49)
> q(16) difficult
Getting Initial Values:
Fitting Full model:
Iteration 0:   log likelihood = -62983.096  (not concave)
Iteration 1:   log likelihood = -58371.105  (not concave)
Iteration 2:   log likelihood = -57742.524  (not concave)
Iteration 3:   log likelihood =  -57633.96
Iteration 4:   log likelihood = -57628.523  (not concave)
Iteration 5:   log likelihood = -57600.409
Iteration 6:   log likelihood = -57586.334
Iteration 7:   log likelihood = -57579.262
Iteration 8:   log likelihood = -57578.997
Iteration 9:   log likelihood = -57578.991
Iteration 10:  log likelihood = -57578.991

Endogenous-Switch Poisson Regression
(16 quadrature points)
                                                  Number of obs   =      19559
                                                  Wald chi2(4)    =    2285.19
Log likelihood = -57578.991                       Prob > chi2     =     0.0000
```

children	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
children						
catholic	-.0355655	.0129769	-2.74	0.006	-.0609998	-.0101311
indspker	-.262709	.0187704	-14.00	0.000	-.2994983	-.2259197
after49	-.0722155	.0099639	-7.25	0.000	-.0917444	-.0526867
edu12	-1.202969	.026841	-44.82	0.000	-1.255576	-1.150361
_cons	2.118149	.0191674	110.51	0.000	2.080581	2.155716
switch						
indspker	-1.09937	.038423	-28.61	0.000	-1.174678	-1.024063
after49	.2901196	.021878	13.26	0.000	.2472394	.3329998
_cons	-.0762112	.016943	-4.50	0.000	-.1094189	-.0430036
sigma	.463215	.0118455	39.10	0.000	.4405704	.4870234
rho	.9539426	.0102186	93.35	0.000	.9290369	.9702421

Excluding `indspker`, no sign changes are detected once endogeneity of `edu12` is considered; however, important differences in the magnitude of the coefficients are found. The impact of `edu12` on the count process is now sensibly higher. Besides, apart from their role on the switch, generation effects contribute less to the reduction of women's completed fertility. Finally, the coefficient on `indspker` becomes negative and significant implying that, once the effect of `indspker` on education has been taken into account, indigenous language is associated with reductions on completed fertility. Moving to the switch part, coefficients on explanatory variables appear to be sensibly lower in the ES specification in relation to the figures obtained from an EXS model. Thus, neglecting the endogeneity of the switch variable appears to result in overestimated coefficients in the switch process.

The parameter ρ is found to be significant and close to unity in the ES specification. By performing a likelihood-ratio test for $\rho = 0$, a $\bar{\chi}^2(01) = -2\,(-57,633 + 57,579) = 108$ statistic is obtained. Thus, the adequacy of the endogenous switching specification is supported by the rejection of the null hypothesis $\rho = 0$ in a boundary-value likelihood-ratio test at any standard confidence level ($\Pr \geq \bar{\chi}^2(01) = 0.0000$). The two models can also be compared using an Akaike information criterion (AIC) statistic. In the case of the EXS model, an $\text{AIC}_{\text{exs}} = 2(57,633) + 2(9) = 115,344$ statistic is found. Similarly, for the ES model an $\text{AIC}_{\text{es}} = 2(57,579) + 2(10) = 115,178$ statistic is reported. On these grounds, the ES model is once again preferred as $\text{AIC}_{\text{es}} < \text{AIC}_{\text{exs}}$.

Although there is no intuitive explanation for a high ρ in the fertility context, the reader should note that Terza (1998) and Greene (1997) obtain high estimates of ρ—near to unity—in similar implementations of an endogenous switching count model. Whether data features in all the three studies induce a high ρ or a high ρ is a tendency of the econometric technique, is not clear.

5 Final comments

This paper presents code for fitting a FIML endogenous switching Poisson count model for cross-sectional data in Stata 7: the `espoisson` command. Results from an illustrative exercise find that an endogenous switching model fits the data better than a model in which the switch is governed by an exogenous process. In addition, it is found that neglecting for the potential endogeneity of a regime-switch variable might result in important bias in both the count and the switching process. The correlation coefficient between the two unobserved heterogeneity terms considered by the model—one for the count, one for the switch—is reported to be near unity. It is not clear if data-specific features induced a high ρ or if a high ρ is rather a tendency of the econometric technique.

The `espoisson` command is implemented using an `ml d0` method. As a consequence, robust standard errors are not currently available. However, since the likelihood function meets the linear-form restriction, an `ml lf` method is in principle possible. Under such an alternative, robust standard errors would be available, and some gains in speed might be obtained. Two extensions are possible: sample selection and zero-inflated models. Both extended models can be implemented with relatively minor modifications to the `espoisson` code.

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7 References

Arulampalam, W. and A. Booth. 1997. Who gets over the training hurdle? A study of the training experiences of young men and women in Britain. *Journal of Population Economics* 10: 197–217.

Cameron, A. and F. Windmeijer. 1996. R-squared measures for count data regression models with applications to health-care utilization. *Journal of Business and Economic Statistics* 14(2): 209–220.

Cook, R. and W. Wei. 2002. Selection effects in randomized trials with count data. *Statistics in Medicine* 21(4): 515–531.

Egel, B. and J. T. Brake. 1993. Analysis of embryonic development with a model for under—or over—dispersion relative to binomial variation. *Biometrics* 49(1): 269–279.

Evans, W. 1989. Deregulation and airline safety: Evidence from count data models. Department of Economics, University of Maryland. Working Paper Series 89(12).

Faria, A., P. Fenn, and A. Bruce. 2003. A count data model of technology adoption. *Journal of Technology Transfer* 28(1): 63–79.

Feinstein, J. 1989. The safety regulations of U.S. nuclear power plants: Violations, inspections, and abnormal occurrences. *Journal of Political Economy* 97: 115–154.

Greene, W. H. 1994. Accounting for excess zeros and sample selection in Poisson and negative binomial regression models. Department of Economics, Stern School of Business, New York University. Working Paper Series EC-94(10).

—. 1997. FIML estimation of sample selection models for count data. Stern School of Business, New York University. Manuscript.

—. 2003. *Econometric Analysis*. 5th ed. Upper Saddle River, NJ: Prentice–Hall.

Gurmu, S. 1997. Semi-parametric estimation of hurdle regression models with an application to medicaid utilization. *Journal of Applied Econometrics* 12(3): 225–243.

Gutierrez, R. G., S. Carter, and D. M. Drukker. 2001. sg160: On boundary-value likelihood-ratio tests. *Stata Technical Bulletin* 60: 15–18. In *Stata Technical Bulletin Reprints*, vol. 10, 269–273. College Station, TX: Stata Press.

Hausman, J., B. Hall, and Z. Griliches. 1993. Econometric models for count data with an application to the patents-R&D relationship. In *The Econometrics of Panel Data*, vol. 2. Elgar Reference Collection Series.

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

INEGI. 2001. Sistema de indicadores para el seguimiento de la situacion de la mujer en Mexico. Information available at *http://www.inegi.gob.mx*.

Kalwij, A. 2000. The effects of female employment status on the presence and number of children. *Journal of Population Economics* 12(2): 221–239.

Kianifard, F. and P. Gallo. 1995. Poisson regression analysis in clinical research. *Journal of Biopharmaceutical Statistics* 5(1): 115–129.

Lee, A., M. Stevenson, and K. Wong. 2002. Modeling young driver vehicle chases: Data with extra zeros. *Accident Analysis and Prevention* 34(4): 515–521.

Melkersson, M. and D. Rooth. 2002. Modeling female fertility using inflated count data models. *Journal of Population Economics* 13(2): 189–203.

Minchener, R. and C. Tighe. 1992. A Poisson regression model of highway fatalities. *American Economic Review* 82: 452–456.

Mullahy, J. 1997. Instrumental-variable estimation of count data models: Applications to models of cigarette smoking behavior. *The Review of Economics and Statistics* 79(4): 586–593.

Santos, J. and F. Covas. 2000. A modified hurdle model for completed fertility. *Journal of Population Economics* 13(2): 173–188.

Self, S. and K. Liang. 1987. Asymptotic properties of maximum likelihood estimators and likelihood-ratio test under nonstandard conditions. *Journal of the American Statistical Association* 82(398): 605–610.

Terza, J. 1998. Estimating count data models with endogenous switching: Sample selection and endogenous treatment effects. *Journal of Econometrics* 84: 129–154.

Wang, W. and F. Famoye. 1997. Modeling household fertility decisions with generalized Poisson regression. *Journal of Population Economics* 10(3): 273–283.

Willis, R. 1973. A new approach to the economic theory of fertility behavior. *Journal of Political Economy* 81(2): s14–s64.

Windmeijer, F. and J. Santos. 1997. Endogeneity in count data models: An application to demand for health care. *Journal of Applied Econometrics* 12(3): 281–294.

Winkelmann, R. 1996. Count data models with selectivity. University of Canterbury, Christchurch, New Zealand. Manuscript.

—. 2001. *Econometric Analysis of Count Data*. 3d ed. Berlin: Springer.

Yen, S. 1999. Gaussian versus count data hurdle models: Cigarette consumption by women in the U.S. *Economics Letters* 6: 73–76.

About the Author

Alfonso Miranda is a PhD student at the Economics Department of Warwick University. His research interests include population economics, health economics, and econometrics.