Random Parameters and Self–Selection Models

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Abstract

In this paper I discuss the specification of self–selection models with random parameters. I demonstrate that in a self–selection model, misspecification of the parameter structure as constant causes biased estimates, and the direction of the bias leads to an under–estimation of the selectivity effect. I estimate a self–selection model of moonlighting with random parameters and find that the selectivity effect, which was almost absent in the constant parameter version of the model, is indeed significant.

I. Introduction

The general linear model is usually specified with constant parameters. It has been argued that this is not a valid assumption if there is variation in tastes across a cross–section of the population or variation in time across a time–series of data. Another argument against constant parameters is made in optimization problems that involve policy variables. As Maddala(1977) points out, constant parameters imply that changes in policy create a one–time average response. If people do take into account possible changes in policy, these changes ought to affect both the dependent variable and the parameters of the decision function.

Varying parameter models are popular in pooled time–series cross–section models and adaptive regression models. However, inspite of the convincing arguments made for them, the case for introducing them into the general linear model is weak. Even if the parameters are misspecified as constant, the estimates are consistent. It has also been pointed out that if the assumption of homogeneous cross–section units is invalid, measurement and other errors probably dominate the effects of differences in tastes, thus reducing the need for varying parameters that might capture the differences across the cross–section. With limited data, and quantities varying continuously, it seems pointless to argue in favour of a more complicated specification that would not improve the estimates.

This paper examines the case for varying parameters in a self–selection model. In this case, the arguments for varying parameters cannot be readily dismissed. The premise of a self–selection model is that people have different abilities and tastes that drive them to their choices; this is inconsistent with a constant parameter specification. More important, it turns out that misspecification of parameters is costly in a self–selection model since estimates will be biased and inconsistent as a result.

In the general linear model, misspecifying the parameters as constant gives consistent but inefficient estimates. This is because the true error structure is heteroscedastic, and if ignored causes inefficient estimates. The same misspecification in a self–selection model causes the same problem; the errors are heteroscedastic. However, unlike the general linear model, heteroscedastic errors in a self–selection model cause biased and inconsistent estimates. This problem was examined by Maddala and Nelson(1975) and Hurd(1979). They find that even modest heteroscedasticity can cause substantial bias in parameters. It seems far more sensible to make some reasonable assumptions about the nature of the heteroscedasticity rather than ignore it. Since the problem of misspecified parameters reduces to that of neglecting the heteroscedasticity in the errors, it is important to pay more attention to the parameter structure in a self–selection model than one would in the usual linear model.

The only paper that dwells on this problem is a working paper by Selen(1981). He argues that self–selection models ought to be specified with varying parameters and estimates a model of migration choice with random parameters. In this paper, I extend his analysis and discuss the nature and direction of the bias created by misspecification and estimate a double self–selection model of moonlighting with random parameters.

Other studies in the area are by Hausman and Wise(1978) and Akin, Guilkey and Sickles(1979). Hausman and Wise developed their model for a discussion of transit choice, in order to avoid the problems of the independence of irrelevant alternatives in McFadden's(1973) conditional logit model. Their model is a probit with varying parameters that allows correlation among the error terms of choice functions. They find that the predicted effects of introducing a new mode of travel are different from the predictions offered by the conditional logit model.

Akin, Guilkey and Sickles estimate an ordered response analogue of the conditional probit model in a study of family migration. They include varying parameters to capture the differences in the decision–making process across families and to estimate the heterogeneous effects on the decision to migrate.

The next section contrasts a simple self–selection model with constant parameters with a random parameter self–selection model. I examine the biases wrought through misspecification and the possible direction the bias might take. The final section examines a random parameter self–selection model of moonlighting and discusses the estimates.

II. The Self–Selection Models Compared.

In this section, I present a simple model of self–selection with constant parameters and contrast it with the random parameter version of the model. The constant parameter model accounts only for the bias due to self selection; the random parameter model accounts for both the selectivity bias and the bias due to the heteroscedasticity caused by the random parameters.

A Simple Model of Self–Selection With Random Parameters:

A self–selection model is defined by a participation function that allows one to discriminate between groups. The introduction of random parameters into the participation function is justified by the differing tastes in the population that prompt people to choose different groups.

Consider the participation function denoted by I.

$$I_i = \begin{cases} 1 & \text{if the } i^{th} \text{ person chooses group 1} \\ 0 & \text{if he chooses group 2} \end{cases}$$

Let I_i^* denote the function of exogenous variables $Z_i(k\times 1)$, that influence the participation decision I_i. This function is specified with random parameters.

$$I_i^* = Z_i\alpha_i - u_i \qquad i = 1,n$$

$$\alpha_{ij} = a_j + v_{ij} \qquad j = 1,k$$

$$I_i^* = Z_i a + Z_i v_i - u_i$$

Let $u_{iR} = Z_i v_i - u_i$. Then the participation function can be written thus:

$$I_i = \begin{cases} 1 & \text{if } I_i^* > 0 \text{ or } Z_i a + u_{iR} > 0 \\ 0 & \text{if } \qquad Z_i a + u_{iR} < 0 \end{cases} \qquad (1)$$

(the hours worked for instance, in a problem of labour force participation), are described by the behavioral functions. These functions are specified with constant parameters since they can be estimated consistently by OLS. Denote the vector of attributes in group 1 by y_1 and that of group 2 by y_2.

$$y_{1i} = X_{1i}\beta_1 - e_{1i} \qquad i = 1,n_1 \qquad (2)$$

$$y_{2i} = X_{2i}\beta_2 - e_{2i} \qquad i = 1.n_2 \qquad (3)$$

The complete model consists of the participation function and the two behavioral equations. The model can be estimated using Heckman's(1976) two–step method. In order to obtain consistent estimates I make the following assumptions.

Assumptions:

1. a) $u_i \simeq N(0,1) \qquad i = 1,n$

   b) $E(v_i) = 0. \qquad Cov(v_{ij}, v_{i'j'}) = \begin{cases} 0 & \text{for all } i \neq i', j \neq j' \\ 1 & \text{for all } i, i' \quad j = j' \end{cases}$

2. $Cov(u_i, e_{lm}) = \sigma_{ul}^2 \qquad l = 1.2$ and for all i,m.

3. a) $Cov(u_i, v_i) = 0 \qquad$ for all i.

   b) $Cov(v_i, e_{lm}) = 0 \qquad$ for all i,l,m.

4. $Cov(e_{1i}, e_{2j}) = \sigma_{12}^2 \qquad V(e_{li}) = \sigma_l^2$

Let Σ_{iR} denote the variance–covariance matrix of (u_{iR}, e_1, e_2)

$$\Sigma_{iR} = \begin{matrix} \sigma_{iuR}^2 & \sigma_{1u}^2 & \sigma_{2u}^2 \\ - & \sigma_1^2 & \sigma_{12}^2 \\ - & - & \sigma_2^2 \end{matrix}$$

$$\sigma_{uiR}^2 = Var(u_{iR}) = Z_i{}'Z_i Var(v_i) + 1$$

The estimates of the parameters α, in the participation function can be obtained using the probit maximum–likelihood method. Once consistent estimates of a_j's and σ_{uiR} are obtained, the parameters in the behavioral function can be estimated. The behavioral equations are re–written to account for the fact that the conditional expectation of the errors e_l is not zero.

Let $W_{1R} = -\varphi(Z_i a/\sigma_{iuR}) \div \sigma_{iuR}(\phi(Z_i a/\sigma_{iuR}))$

Let $W_{2R} = \varphi(Z_i a/\sigma_{iuR}) \div \sigma_{iuR}(1 - \phi(Z_i a/\sigma_{iuR}))$

$E(e_{1i}/ I_i = 1) = -\sigma_{1u}W_{1R} \qquad E(e_{2i}/ I_i = 0) = \sigma_{2u}W_{2R}$

$y_{1i} = X_{1i}\beta_1 + \sigma_{1u}W_{1Ri} + t_{1i} \qquad (2)$

$y_{2i} = X_{2i}\beta_2 + \sigma_{2u}W_{2Ri} + t_{2i} \qquad (3)$

Each of these equations can be estimated by least squares methods. The method presented by Lee and Trost(1978) in order to get efficient estimates. This method guarantees that estimates of the standard errors will be positive.

The Self–Selection Model With Constant Parameters:

This is the standard self–selection model but it is necessary to display it once more to compare it with its random parameter counterpart. The same notation is used in this model.

Consider the participation function denoted by I.

$$I_i = \begin{matrix} 1 & \text{if the } i^{th} \text{ person chooses group 1} \\ 0 & \text{if he chooses group 2} \end{matrix}$$

Let I_i^* denote the function of exogenous variables $Z_i(k\times1)$, that influence the participation decision I_i. This function is specified with constant parameters.

$I_i^* = Z_i\alpha_i - u_i \qquad i = 1,n \qquad (1')$

Denote the vector of attributes in group 1 by y_1 and that of group 2 by y_2.

$y_{1i} = X_{1i}\beta_1 - e_{1i} \qquad i = 1,n_1 \qquad (2')$

$y_{2i} = X_{2i}\beta_2 - e_{2i} \qquad i = 1.n_2 \qquad (3')$

The complete model consists of the participation function and the two behavioral equations. Let Σ denote the variance–covariance matrix of (u_i, e_1, e_2)

$$\Sigma = \begin{matrix} 1 & \sigma_{1u}^2 & \sigma_{2u}^2 \\ - & \sigma_1^2 & \sigma_{12}^2 \\ - & - & \sigma_2^2 \end{matrix}$$

Notice that the matrix Σ is no longer indexed by i. As before σ_{12} is not estimable but estimates of the other parameters can be obtained. The behavioral equations are re–written to account for the fact that the conditional expectation of the errors e_1 is not zero.

Let $W_1 = -\varphi(Z_i\alpha) \div \phi(Z_i\alpha)$

Let $W_2 = \varphi(Z_i\alpha) \div (1 - \phi(Z_i\alpha))$

$E(e_{1i}/\ I_i = 1) = -\ \sigma_{1u}W_1 \qquad E(e_{2i}/\ I_i = 0) = \sigma_{2u}W_2$

$y_{1i} = X_{1i}\beta_1 + \sigma_{1u}W_{1i} + w_{1i} \qquad (2')$

$y_{2i} = X_{2i}\beta_2 + \sigma_{2u}W_{2i} + w_{2i} \qquad (3')$

Each of these equations can be estimated by least squares methods as before.

The difference between the specifications is due to the variables associated with the coefficients of selectivity bias, σ_{lu} $l = 1,2$. If constant rather than random parameters are used the independent variables $(W_{1R,}\ W_{2R})$ are being misspecified as (W_1, W_2). This is the errors–in–variables problem and its consequences are discussed below.

Denote the estimate of σ_{1u} obtained from equation (1') by s_{1u}. I assume that the true specification is given by (1). The OLS estimation of (1') results in the following expression.

$$E(s_{1u}) = \sigma_{1u}(\ (W_1'W_1 - W_1'X_1(X_1'X_1)^{-1}X_1'W_1)^{-1}(W_1'W_{1R}$$
$$-W_1'X_1(X_1'X_1)^{-1}X_1W_{1R}))$$

Let $M = I - X_1(X_1'X_1)^{-1}X_1$

$$E(s_{1u}) = ((W_1'M\ W_{1R}) \div (W_1'M\ W_1))\ \sigma_{1u}$$

Since the $\mathrm{Var}(u_{iR}) > 1$, the quantity $W_1'M\ W_{1R}$ is less than $W_1'M\ W_1$ and therefore the estimate of selectivity bias obtained from the constant parameter specification will understate the true selectivity bias σ_{1u}. This is likely to be worse if the participation function and the behavioral equation have variables in common as is often the case. This implies that the economist could well conclude that the selectivity bias (using a t–test to check H_0: $\sigma_{1u} = 0$), is insignificant.

However, it turns out that if one does favour a random parameter specification, it is not readily possible to conduct a specification test in the usual fashion and therefore one is forced to presume that the random parameters represent the true model. A specification test would involve testing the null hypothesis that the parameters have a variance of zero. The difficulty with testing this null hypothesis is that the true value of the parameters being tested lie on the boundary of the parameter space. In such cases, the maximum likelihood estimator of the true variance vector is not asymptotically normally distributed under the null hypothesis. This means that the distribution of the Likelihood Ratio and Wald test statistics are not the usual chi–squared distributions but a mixture of distributions instead. The Lagrange Multiplier test does have the usual properties under the null(Breusch and Pagan,1979) but it ignores the one–sided nature of the alternative and therefore has lower power than other test statistics that do take account of this. Another option is the Score Test developed by Chesher(1984) for the problem of neglected heterogeneity. The advantage to his approach is that it does not require an arbitrary specification of the distribution of varying parameters.

III. A Double Self–Selection Model of Moonlighting With Random Parameters

The model describes the decision to moonlight by married men. I assume that the husband and wife jointly maximize a household utility function. Thus, the husband's decision to moonlight and the wife's decision to work are related. I also obtain labour supply functions for the husband on the second job that differ depending on whether his wife works. This model was originally estimated with constant parameters by the author (Krishnan,1989) and details of the complete derivation of the model can be found in that paper. One of the features of the specification is that instead of using the usual variables, years of schooling and years of experience, to capture the effects of general and specific human capital investment, I developed proxies based on the general and specific skills required on the first job. The information on skill requirements for each occupation was obtained from the Dictionary of Occupational Titles. The motivation for creating such proxies is that the usual variables cannot explain the heterogeneity in wages that arise from different kinds of training.

The model consists of two participation functions and two sets of behavioral equations. These functions are obtained from the maximization of the household utility function subject budget and time constraints.

Let h_1,h_2 = hours of work by the moonlighter on the first and second jobs respectively.

w_1,w_2 = wage rates on the first and second jobs.

f = wife's hours of work $\qquad w_f$ = wife's wage rate.

Let L_m, L_f denote the participation decisions of husband and wife.

$$L_m = \begin{cases} 0 & \text{if } h_2 = 0 \text{ or } R_1(f) < 0 \\ 1 & \text{if } h_2 > 0 \text{ or } R_2(f) > 0 \end{cases} \qquad (1)$$

$$L_f = \begin{cases} 0 & \text{if } f = 0 \text{ or } R_2(h_2) < 0 \\ 1 & \text{if } f > 0 \text{ or } R_2(h_2) > 0 \end{cases} \qquad (2)$$

R_1 and R_2 are the latent functions of exogenous variables that influence the participation functions. They are a correlated system of equations and I assume that the errors have a bivariate normal error structure. Furthermore, the parameters are assumed to be random variables.

$$R_1(f) = Z_m\alpha_m - u_m \qquad \alpha_{mij} = a_{mj} + v_{mij} \quad i = 1,n \quad j = 1,k_m$$

$$R_2(h_2) = Z_f\alpha_f - u_f \qquad \alpha_{fik} = a_{fk} + v_{fik} \quad i = 1,n \quad k = 1,k_f$$

If the husband does moonlight (i.e. if $h_2 > 0$), his labour supply functions fall under different regimes depending on whether his wife works. Let (h_2,w_2) represent the hours and wages on the second job if she does not work and (h_2^f,w_2^f) be his hours worked and his wages if she does decide to work.

Regime 1: $L_m = 1 \quad L_f = 1$

$h_2^f = X_{1f}\beta_{1f} - e_{1f}$ (1a)

$w_2^f = X_{2f}\beta_{2f} - e_{2f}$ (1b)

X_{1f}, X_{2f} are vectors of exogenous and endogenous variables that include w_2^f, h_2 and f since (h_2^f, w_2^f) is a simultaneous equation system.

Regime 2: $L_m = 1 \quad L_f = 0$

$h_2 = X_1\beta_1 - e_1$ (2a)

$w_2 = X_2\beta_2 - e_2$ (2b)

The complete model is a double self–selection system consisting of the participation functions (1,2) and the behavioral functions (1a,1b) and (2a,2b). This system was estimated using a two–step method where the participation functions were estimated by bivariate probit method and the behavioral functions by 2SLS after correcting for selectivity and parameter specification bias.

Table 1

Characteristics of SIPP sample of Married Couples

Characteristics	SS = 4448	$L_m=1$ $L_f=1$ SS = 126	$L_m=1$ $L_f=0$ SS = 93
Hours on primary job/week	42.313 (9.066)	40.460 (9.988)	40.054 (13.126)
Hours on second job/week		23.651 (18.058)	26.785 (19.525)
Wage on primary job/hour	11.667 (7.599)	10.095 (5.662)	14.033 (22.167)
Wage on second job/hour		9.211 (6.063)	13.140 (22.523)
Wife's wage rate		6.749 (4.721)	
Wife's hours		31.413 12.321	
Family property income/month	120.832 (467.319)	146.103 (452.502)	299.839 (1059.64)
Children under 18	1.140 (1.200)	1.330 (1.081)	1.591 (1.416)
Husband's age	42.714 (11.750)	38.317 (10.222)	39.505 (12.647)
Wife's age	40.182 (11.760)	36.563 (10.319)	37.624 (12.152)

Standard deviation in parentheses

IV.Data and Results

The model was applied to a sample of 4448 married couples from the U.S. Survey of Income and Program Participation (Wave 2). Two hundred and nineteen men held (4.9% of the sample) second jobs.A comparison of the mean characteristics for these groups is in Table 1. The entire group worked an average of 42 hours per week, earning an average wage of $11.66. Moonlighters work fewer hours on the first job on average, but work longer hours in total. They are younger on average, and have larger families. In the sample, moonlighters are mostly in primary occupations like management, police, construction, sales and teaching. Managers and construction workers constitute 18% of all moonlighters. These occupations are also the second jobs most often chosen.

he estimates of the participation functions for husband and wife are in Tables 2 and 3. The estimates are similar in sign to the constant parameter version and are subject to much the same interpretation. In this paper, I concentrate on the differences in estimates between the constant and random parameter versions of the model. The value of the likelihood function indicates that the random parameter specification of the participation function in particular does not offer a significant improvement over the constant parameter model. However, some estimates are different and in some case appear to have an inexplicable sign in the constant parameter version. This lends credence to the idea that random parameters allow for a better interpretation of the model.

The standard deviation of the estimates is significant for the variables, income and hours on the first job, the dummies urban and race and the proxies for human capital investment. In short, there is evidence of random fluctuation around the mean values of the parameters in these cases, dictated by the unobserved differences between households. It indicates that the decision–making process varies between households and provides an estimate of the range of variation. An improvement over the constant parameter version is provided by the unemployment rate. This is supposed to serve as a proxy for the costs of participation and ought to deter participation, if high. The random parameter estimate is

Table 2
Random Parameter Estimates of Participation Functions L_m

Variable	Estimate	Standard Deviation
Intercept	–0.352 (0.003)	0.512 (0.004)
Ln (Husband's Income)	–0.320 (0.002)	0.026* (0.001)
Non–Labor Income	0.00025 (0.0005)	0.0014 (0.063)
Number of children	0.089 (0.006)	0.0006 (1.020)
Husband's hours on first job	–0.012 (0.0005)	0.003* (0.004)
Urban (=1)	0.029 (0.00)	0.191 (0.044)
Unemployment Rate	–0.051 (0.003)	0.005 (0.007)
Own age	0.064 (0.002)	0.0001 (0.103)
Own race	0.167 (0.007)	0.072 (0.784)
Genrl. Training (GTS,GTE)	0.004,–0.091 (0.002,0.001)	0.124.0.025* (.0002,.0001)
Specific Training	–0.009 (0.0003)	0.003 (0.002)
First occupation		(services = base)
Professional	0.018 (0.008)	0.001 (0.0002)
Sales,technical	0.156 (0.001)	0.224 (0.026)

Table 3

Random Parameter Estimates of Participation Function L_f

Variable	Estimate	Standard Deviation
Intercept	1.722 (0.0004)	0.878 (0.972)
Ln (Husband's Income)	–0.269 (0.071)	0.088 (0.088)
Non–Labor Income	–0.00059 (0.0002)	0.00 (0.474)
Number of children	–0.590 (0.236)	0.445 (0.530)
Husband's hours on first job	0.052 (0.023)	–0.035* (0.0002)
Urban (=1)	0.719 (0.00)	3.270* (0.493)
Unemployment Rate	–0.057 (0.161)	–0.033 (0.077)
Own age	–0.530 (0.001)	0.605 (2.131)
Own race	–0.011 (0.074)	–0.001 (7.120)
Years of Schooling	0.136 (0.0002)	0.006 (0.005)

Log Likelihood = –962.660
Correlation between L_m and L_f = –.296 (0.033)

–.05 while the constant parameter version yielded the inexplicable estimate of .01.

The estimate of the related decision function for the wife is in Table 3. One of the interesting results in the random parameter version is the positive coefficient associated with the husband's hours of work. The mean positive value of this parameter suggests that the wife is more likely to work if her husband works longer hours on the first job. This could support the negative value of the correlation coefficient indicating that the husband's and wife's decision are negatively correlated. Therefore, unlike the fixed parameter version, the random parameter yields a consistent interpretation of behavior. This indicates that husband and wife are substitutes in household production. Few of the estimates in this function have significant standard deviations. Differences in tastes are probably dominated by other considerations like family income and relative productivity at home.

The behavioral relationships were specified with constant parameters since misspecification here is not costly. However, the estimates are inefficient since the heteroscedasticity in errors is ignored. Tables 4 and 5 present the estimates of the behavioral functions after the correction for selectivity bias and bias due to the randomness in parameters is applied. These tables demonstrate that this is indeed significant unlike the constant parameter version where the bias was tentative. This is an important result and indicates that if the researcher does have access to sufficient data, it would be profitable to use a varying parameter specification in a self–selection model. The model structure warrants it and if constant parameters are likely to understate the bias it would be foolish to risk this specification on the grounds that it is less strenuous to estimate.

The estimates of the other parameters of the behavioral functions differ but not substantially. The exception is the variable, family income, in the case where the wife does not work. The constant parameter was significant; in the random parameter version it has been obliterated. In short, the pure income effect is nonexistent in the second job.

Table 4

Random Parameter Estimates of Behavioral Relationship
[Case Where Wife Does Work]
Sample Size =126

Estimates of Hours Function		Estimates of Wage Function	
Variable	Estimate	Variable	Estimate
Intercept	108.141 (30.253)	Intercept	–0.237 (0.385)
Ln Wage2	15.813 (9.440)**	Hours on second job	0.0005 (0.008)
Hours on first job	0.768 (0.248)*	Ln Wage1	0.764 (0.107)*
Urban	.847 (6.221)*	Specific Training	0.016 (0.007)*
Race	7.188 (6.721)	General Training	(–0.013,0.064) (0.012,0.045)
Ln Family Income	–20.740 (7.332)*	Urban	–0.020 (0.086)
Number of children	–0.659 (1.680)	Race	–0.100 (0.161)
Ln wife's wage rate	–1.787 (3.110)		
Correction for bias (L_m)	–0.877 (0.589)***	Correction for bias (L_m)	0.021 (0.014)***
Correction for bias (L_f)	1.105 (3.740)	Correction for bias (L_f)	–0.011 (0.093)
$R^2 = 0.154$		$R^2 = 0.506$	

Table 5

Random Parameter Estimates of Behavioral Relationship
[Case Where Wife Does Not Work]
Sample Size =93

Estimates of Hours Function		Estimates of Wage Function	
Variable	Estimate	Variable	Estimate
Intercept	12.182 (26.732)	Intercept	–0.383 (0.299)
Ln Wage2	8.100 (6.241)**	Hours on second job	0.011 (0.008)
Hours on first job	0.573 (0.186)*	Ln Wage1	0.914 (0.066)*
Urban	10.162 (4.440)*	Specific Training	0.010 (0.005)*
Race	10.733 (9.650)	General Training	(0.005,–0.011) (0.014,0.042)
Ln Family Income	–5.656 (5.176)*	Urban	–0.126 (0.136)
Number of children	–0.636 (1.349)	Race	–0.247 (0.213)
Correction for bias (L_m)	0.927 (14.660)	Correction for bias (L_m)	–0.077 (0.036)*
Correction for bias (L_f)	–1.311 (0.790)**	Correction for bias (L_f)	–0.002 (0.023)
R^2 = 0.207		R^2 = 0.757	

*Significant at the 5% level
**Significant at the 10% level
***Significant at the 15%level
Standard deviation in parentheses

IV. Conclusions

In this paper, I have argued in favour of a varying parameter specification in self–selection models. It seems to be necessary to avoid biased estimates and to allow the researcher more latitude in the interpretation of the estimates. I have established that the selectivity bias is likely to be understated in a constant parameter self–selection model.

This synthesis of random parameters and self–selection models is illustrated in a study of moonlighting. The random parameter version demonstrated the existence of a significant selectivity effect; this bias was clearly understated in the constant parameter version. The random parameter model also allowed for a full–bodied explanation of the decision–making process in a family.

References

Akin, J., Guilkey, D.K., and Sickles, R. 1979, A Random Coefficient Probit Model With an Application to a Study of Migration, Journal of Econometrics, 11: 233–46.

Hausman, J.A., and Wise, D.A., 1978, A Conditional Probit Model for Qualitative Choice: Discrete Decisions Recognizing Interdependence and Heterogeneous Preferences, Econometrica, 46: 319–39.

Heckman, J., 1976, The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models, Annals of Economic and Social Measurement 5:475–92.

Hurd, M., 1979, Estimation in Truncated Samples When There is Heteroscedasticity, Journal of Econometrics, 11:247–58.

Krishnan, P., 1989, The Economics of Moonlighting: A Double Self–Selection Model, Discussion Paper of Centre for Econometrics, University of Florida.

Lee, L.f., and Trost, R.P., 1978, Estimation of Some Limited Dependent Variable Models With An Application to Housing Demand, Journal of Econometrics, 8:357–82.

McFadden, D.,1973, Conditional Logit Analysis of Qualitative Choice Behavior, In P. Zarembka(ed.), Frontiers in Econometrics, New York: Academic Press.

Maddala, G.S., 1977, Econometrics, New York: McGraw–Hill.

________________ 1983, Limited Dependent and Qualitative Variables in

Econometrics, New York: Cambridge University Press.

Maddala, G.S., and Nelson, F., 1975, Switching Regression Models With Exogenous and Endogenous Switching, Proceedings of the American Statistical Association:423–6.

Selen, J., 1981, Random Parameters and Selectivity Adjustment for the Linear Model, Working Paper of the Swedish Institute for Social Research, Stockholm.