Discussion paper No. 2003/05
Department of Economics
University of Osnabrück

Observable and non-observable social interactions in labor supply

Johannes Jaenicke

Rev. Version, May 2004

Department of Economics
University of Osnabrück
D-49069 Osnabrück

Observable and non-observable social interactions in labor supply

JOHANNES JAENICKE*
University of Osnabrück
Rev. Version, May 2004

Abstract

This paper analyzes determinants of individual work force participation in a bivariate probit model using data from the GSOEP. From Monte Carlo simulation, we know that there is low probability to detect social interactions in medium data sets. Nevertheless, we find that apart from influences such as age, number of children and local employment rates, educational and gender differences as well as the work force participation of the eldest brother or sister also have a significant influence on a person's work force participation. The results show that the second-born takes a similar job participation decision as his/her peer.

Key words: Work force participation, social competition, risk sharing, siblings, bivariate probit model

JEL classification: C35, D13, J21, Z13

* *Correspondence:* Johannes Jaenicke, University of Osnabrück, Department of Economics, Rolandstraße 8, D-49069 Osnabrück, Tel.: ++49-541-969-2632, FAX ++49-541-969-2722, E-mail: jaenicke@oec.uni-osnabrueck.de.

The paper uses the Germany version of the German Socio-Economic Panel, which is available under the German data security standards after signing a contract with the German Insitute for Economic Research, DIW, Berlin. The SPSS-code for reading and transforming the variables is available on request from the author.

I would like to thank Giacomo Corneo and Ralf Pauly for their advice and Gerald Musiol, Reinhard Neck, Iris Reiter, György Széll, Joachim Wilde, Peter Winker, and especially Margot Petersen for their help and comments.

1 Introduction

Economic analysis has recently rediscovered the question of social interactions. Traditionally, social interactions have been neglected by economic theory or considered problems of incomplete markets that prevent the economy from achieving a social optimum (Manski, 2000). By now, many economists have come to recognize that social interactions are an important motive for economic behavior as a part of human behavior.

The basis for the analysis of social interactions are reference group effects, behavior in social networks, or herd behavior in a Bayesian learning framework (Bikhchandani, Hirshleifer and Welch, 1992). According to the reference group explanation, an individual's decision is based on his or her own preferences and on the possible deviation of one's own decision from that of one's peer (Akerlof, 1997). A social network may act as a risk-sharing mechanism. For recent empirical evidence favoring risk-sharing within households in rural Ethiopia or in Indian villages, see the studies by Dercon and Krishnan (2000) and Ogaki and Zhang (2001). However, risk-sharing between or within American families is rejected by Hayashi, Altonji and Kotlikoff (1996).

Social interactions may also have an influence on consumer behavior (Corneo and Jeanne, 1999), savings behavior (Cole, Mailath and Postlewaite, 1992), subjective well-being (Clark and Oswald, 1996), or labor supply. With respect to the explanation of labor supply, social norms or family effects are found to be an important factor for the female labor force participation by Murphy (1995). Woittiez and Kapteyn (1998) include habit formation and reference group behavior in their model of female labor supply. They only find weak empirical evidence for the influence of reference groups, but strong influence of habit persistence.

Following Solon, Page and Duncan (2000) and Oreopoulos (2002), neighborhoods may have an influence on educational attainment and the labor market success of youths. The authors ascertain that the correlation of neighboring children is very low in comparison with the correlation of siblings. According to this result, family backgrounds are the main source for educational attainment and long-term labor market success.

From a psychological point of view, Sulloway (2001) shows that the birth order of siblings is an important factor in the explanation of human behavior. Some psychometricians argue that for siblings the shared environment only constitutes a small proportion of environmental influences and that these influences are dominated by the nonshared environment. This means that children may experience the same environment in a different way, or have different formative experiences despite living in the same family (e.g., Murray, 2002).

In this study, we analyze the problem of individual discrete choice in the presence of possible social interactions with the individual's eldest brother or sister. The discrete choice behavior variable is participation in the work force, i.e. we investigate whether a person tends to take a similar or an opposite job participation decision to its elder brother or sister. We use family background information taken from the German Socio-Economic Panel (GSOEP) and raise the question whether risk-sharing within the family or competition between younger and elder siblings may play an important role in the decision. Although a Monte Carlo study by Jaenicke (2003) shows that the power of the applied parameter tests is low in small samples, we find strong empirical evidence for social interactions.

The paper is organized as follows. In the next section, we present the bivariate probit model for the work force participation of siblings and discuss the power of parameter tests in this framework. Section 3 provides the main empirical results for the work force participation in two different waves of the GSOEP. Section 4 concludes.

2 A bivariate probit model for work force participation decisions

Manski (1993) detects problems in identifying endogeneous neighborhood effects in linear regression models of large neighborhoods. The models were not able to distinguish between endogeneous and contextual interactions. Brock and Durlauf (2001, 2002), however, show that this identification problem can be solved in nonlinear discrete choice models if there is sufficient inter-neighborhood variation. Since we look at the question of workforce participation of siblings in a dichotomous way, the Manski critique does not apply to our analysis.

For the researcher, interactions between brothers and sisters may only partly be observable, due to psychological reasons. To detect the neglected or non-observable interactions between the respective decision processes of the individual and his or her eldest brother and sister, we estimate a bivariate probit model for their work force participation and analyze the covariance of the residuals.[1]

The regression equations of the individual I (second-born) and the peer P (first-born) are

$$\begin{aligned} WFP_I^* &= X_I\beta_1 + WFP_P\beta_2 + u_I, & WFP_I = 1 \text{ if } WFP_I^* > 0, 0 \text{ else} \\ WFP_P^* &= X_P\gamma_P + u_P, & WFP_P = 1 \text{ if } WFP_P^* > 0, 0 \text{ else} \\ [u_I, u_P] &\sim \Phi_2(0,0,1,1,\rho), & \end{aligned}$$

with work force participation WFP and exogenous variables X. X contains individual characteristics (such as sex, age, marital status, level of school education, level of parents' education) and other attributes of the decision

[1] The maximum likelihood estimation of a bivariate probit model involves the numerical problem of the evaluation of double integrals over the normal distribution. This estimation procedure is by now implemented in several statistic computer programs (e.g. LIMDEP, STATA, TSP). We used LIMDEP Version 7.0.

process (such as household income the year before, work force participation the year before). The above equations are a recursive[2], simultaneous binary choice model first proposed by Maddala and Lee (1976). As a condition of identification, we need no exclusion restrictions on the exogenous regressors. Wilde (2000) shows that the existence of a varying exogenous regressor is sufficient to avoid small variation identification problems. A recent application of the model can be found in a study by Greene (1998).

In our model, the observable part of the social interactions, the influence of the decision of the peer, is tested by the hypothesis $H_0 : \beta_2 = 0$. The non-observable part of the social interactions may be revealed through the residual covariance structure. A residual covariance $cov\,(u_I, u_P)$, i.e. ρ, significantly different from zero, may serve as an indicator of unobserved social interactions between the two decisions or as an indicator of simultaneously neglected third-party effects. To minimize the latter-mentioned influences, economic variables describing structural effects, such as local employment rates, should be included in the matrices X_I and X_P as long as the covariance $cov\,(u_I, u_P)$ is significantly different from zero.

Gordon, Lin, Osberg and Phipps (1994) conclude from their empirical estimation of dichotomous discrete choice models that it is “desirable to have at least 10,000 observations in order to be reasonably sure of parameter stability in a probit or logit model of labour force participation.” Our empirical data set consists of only 154 pairs of brothers and sisters in the first two waves and 380 in the final wave. Other studies using a bivariate probit model have to deal with even less observations, e.g., Greene (1998) with 132 obsvervations. In order to investigate the small sample behavior of tests in the bivariate probit model, in Jaenicke (2003) we make a small Monte Carlo study. We analyze the power of the usual z-coefficient tests concerning the paramet-

[2]The recursive nature follows from the condition of logical consistency. In the linear simultaneous equation literature the term *recursive* is used for models in which the residuals $[u_I, u_P]$ are independent. In our case, this assumption is not necessary. See Maddala (1983, 119 and 122-123).

ers of the observable and non-observable social interactions, β_2 and ρ. The results show that the power of these tests is very low in a medium sample size of $T = 200$ observations. For example, in the case of $\rho = 0.4$, only 38.4 percent of the true ρ-coefficients and 34.8 percent of the true β_2-coefficients are significantly different from zero at the 5-percent significance level. The power can be dramatically increased if it is possible to find the neglected variables that cause high residual correlation.

3 Empirical results

In the empirical analysis, we restrict ourselves to the binary choice of labor force participation using the first two and the 1999 waves of the GSOEP for a demonstration of our approach. The sample consists of young adults who have one brother or sister also appearing in the panel.[3] 12.0 percent of these adults are immigrants. The dependent variables are the work force participation of the sibling pairs. The work force participation variable is coded one if the person is employed full-time or in vocational training and zero if the person is not gainfully employed. We aim at controlling for some key variables of the work force decision process, including current and lagged variables. In the model selection process, we estimated models with different independent variables such as sex, age, marital status, level of school education, current education or career training, parents' level of education, household income the year before, work force participation the year before, living in the same household. We also consider influences such as local employment rates (using sample information in the GSOEP), differences in the level of school education, and whether the regarded person is of the same sex as his or her sibling. Some descriptive statistics of the chosen variables are presented in table 1. We see, e. g., that the first-born on average is 4 years older and, at the time of the interview, better educated than the second-born.

[3]Brothers and sisters are identified by their parents' number. Neither half brothers and sisters nor persons with two or more brothers or sisters in the data set are selected.

Table 1: Descriptive statistics (1985 wave)

variable	mean	std. dev.	min.	max.
WFP85$_P$	0.792	0.407	0	1
age$_I$	20.013	3.337	17	46
gender differences and birth order$^{1)}_{P-I}$	-0.006	0.736	-1	1
differences in school education$^{2)}_{P-I}$	0.318	1.595	-5	5
age$_P$	22.95	4.031	18	47
differences in age$_{P-I}$	3.976	2.530	0	15
current education, training$_P$	0.675	0.470	1	2
local employment rate$_P$	91.661	2.701	67.400	93.900

[1)] This variable is coded -1, 0, or 1 for elder brother and younger sister, siblings of same sex, or elder sister and younger brother.

[2)] The school education is recoded to a 6-point-scale, with 'No school degree' and 'In school' at the position 0 in order to obtain an ordinal rank scale.

The final estimation results of the bivariate probit model for the 1985 wave are presented in table 2. All parameters are significantly different from zero. Since there are only 154 observations, the inclusion of non-significant variables is avoided.

In our data set, we find that apart from age, age squared, and local employment rates, the work force participation of the elder brother or sister as well as educational and gender differences are significant and observable social influences in the labor market decision. The work force probability is U-shaped in age, but only the increasing part of the function is relevant for our sample. Neither the individual's level of school education nor the sex of the first- or second-born are significant variables, possibly because of the low power of the test. Comparison of the siblings in these aspects, however, gives a significant explanation of their work force behavior. These interaction variables are able to absorb the significant correlations of the residuals between both decision equations.

Table 2: A bivariate probit model for the work force participation of siblings (1985 wave)

variable	**coefficient**	**marginal effects for** $E\left[WFP_I \mid WFP_P = 1\right]$	**mean of** X
	WFP85^*_I-equation		
age_I	-0.163***	-0.655	20.013
$(\text{age}_I)^2$	0.006**	0.002	411.584
WFP85_P	1.204**	0.485	0.792
gender differences and birth order$_{P-I}$	-0.321**	-0.129	-0.006
differences in the level of school education$_{P-I}$	-0.125*	-0.050	0.318
	WFP85^*_P-equation		
age_P	-0.069***	-0.003	22.955
current education, training$_P$	1.601***	0.058	0.675
local employment rate$_P$	0.017***	0.001	91.661
ρ	-0.250		
Nobs, LogL	154	-153.337	
count actual/predicted	$\text{WFP85}^*_P = 0$	$\text{WFP85}^*_P = 1$	total
$\text{WFP85}^*_I = 0$	23/6	49/49	72/55
$\text{WFP85}^*_I = 1$	9/12	73/83	82/99
total	32/18	122/136	154/154
equal WFP actual/predicted	96/93		
unequal WFP actual/predicted	58/61		

'*','**', or '***' denote that the parameters are significantly different from zero at the 10 percent, 5 percent, or 1 percent levels, respectively.

The results show that a person tends to take a similar job participation decision as its peer, i.e. its elder brother or sister, and not vice versa. The inverse relationship is not significant. The conditional probability for the second-born's job market participation, given the participation of the first-born, is $E\left[WFP_I|WFP_P=1\right]=0.524$. A less educated peer has a negative influence on a person's job participation decision, but the marginal effect, evaluated at the mean of the data, is rather small. We show that the gender difference between the decision-maker and his or her peer has an important impact on the decision about participation in the work force. For a man, an elder sister has a pronounced negative influence on his job participation probability, and vice versa. This fact - surprising at first glance - probably reflects the traditional male-female role behavior, caused by gender-specific differences in education that make women have a lower work force probability.

The joint frequency table reveals that we have a very good fit for equal and unequal job participation behavior. In the case of the participation of the first-born and the non-participation of the second-born, the model perfectly estimates 49 decisions. But the frequency table also shows that the model underestimates the non-participation decision for both groups. This is especially true for the joint non-participation decision.

If we include the work force participation of the year before in the decision equation for the first-born, the signs of the model parameter in our preferred model remain unchanged, but the variable own age and local employment rate become insignificant. If we also include the past work force participation of the second-born, the second-born's age and the social comparison variables also become insignificant. We suppose that this happens because the influence of age and social interactions were already included in the decision one year before. Hence the past endogeneous variable absorbs other influences on the second-born's decision and only explains the persistence of the work force status. We therefore exclude the individual's past work force participation in the final model.

Our estimation results are quite robust against time changes. We also estimate the model presented in table 2 for the 1984 wave using a balanced sample. The signs of the parameters remain unchanged and, once again, the residual correlation is not significant. With a likelihood ratio test, the hypothesis that the parameters are equal in both estimations cannot be rejected at the 10 percent significance level. In 1984, only one parameter out of eight is not significantly different from zero. The exception is the parameter for the local employment rate. Finally, the prediction frequencies are quite good. The model predicts 87.0 percent of all simultaneous decisions correctly. Equal work force participation behavior is predicted in 95 out of 96, unequal behavior in 59 instead of in 58 cases.

Our findings, however, are not robust enough to compensate for social, political and economic changes such as increasing individualism, coaching of women and, last but not least, German reunification. The latter involves the inclusion of the new *Länder* in the data set, with persons interviewed being socialized in a completely different way. Nevertheless, the main results remain stable.

We use an enlarged set of possible explanatory variables for 380 pairs of siblings in the year 1999. 177 out of those interviewed live in the new and 583 in the old *Länder*. 18.4 percent are not of German nationality. On average, the first-born and the second-born are now 27.8 and 23.8 years old, respectively, i.e. they are 3.7 or 4.7 years older than in the 1985 wave. The first-born again has a higher school certificate and higher personal income, however with a high standard deviation in income differences between the siblings. The number of children in the household of the first-born is only 0.2 childs. Detailed descriptive statistics are presented in table 3.

The estimation results for the 1999 wave are presented in table 4. In addition to the final model in 1985, we include, among other things, the number of children, the monthly net household income, and the difference in the personal gross income between the first- and the second-born in 1998. All variables as well as the residual correlation ρ are significantly different from zero. Hence, fitting separate probit models for the first- and the second-born's decision equation can involve significant endogeneity biases in the estimation (Lollivier, 2001). Restricting the residual correlation to zero and therefore excluding non-observable interactions causes a 3.3 percentage points lower prediction quality of the model.

Table 3: Descriptive statistics (1999 wave)				
variable	mean	std. dev	min.	max.
WFP99$_P$	0.724	0.448	0	1
age$_I$	23.774	5.587	17	46
sex$_I$	0.442	0.497	0	1
gender differences and birth order$_{P-I}$	-0.032	0.696	-1	1
living in the same household	0.361	0.480	0	1
number of children in household$_I$	0.116	0.420	0	3
differences in school education$_{P-I}$	0.442	1.606	-5	5
monthly net household income$_I$	4886.23	2572.38	0	22000
differences in the personal monthly gross income 1998$_{P-I}$	573.37	2642.11	-11700	14000
age$_P$	27.750	6.032	18	50
differences in age$_{P-I}$	3.976	2.530	0	15
current education, training$_P$	1.729	0.445	1	2
number of children in household$_P$	0.221	0.602	0	3
education of the mother[1)]	2.416	1.788	1	7
local employment rate$_P$	87.098	4.729	77.070	92.424
[1)]Education of the mother is recoded in order to get an ordinal 7-point-scale.				

The residual correlation ρ may serve as an indicator of unobserved social interactions between the two decisions or as an indicator of simultaneously neglected third-party effects. Although we tried many possible explanatory variables, the residual correlation remains negative and significant. The negative correlation implies that if the work force probability is overestimated in one equation, it is underestimated in the other. This means that here exists a risk-sharing mechanism in the work force participation due to unobservable social interactions. If a common neglected variable exists for both decisions, it has opposite influences on the first- and the second-born's decision.

Table 4: A bivariate probit model for the work force participation of siblings (1999 wave)

variable	coefficient	marginal effects for $E\left[WFP_I \mid WFP_P = 1\right]$	mean of X
	WFP99_I^*-equation		
WFP99_P	0.847**	0.322	0.724
age_I	0.023*	0.009	23.774
sex_I	-0.665***	-0.253	0.442
gender differences and birth order$_{P-I}$	-0.267*	-0.102	-0.032
siblings living in the same household	-0.785***	-.299	0.361
number of children in household$_I$	-0.648***	-0.247	0.116
differences in school education$_{P-I}$	-0.125***	-0.048	0.442
monthly net household income$_I$	0.00004**	0.00002	4886.23
differences in the personal monthly gross income 1998$_{P-I}$	-0.0002***	-0.0001	573.37
	WFP99_P^*-equation		
age_P	0.056***	0.004	27.750
differences in age$_{P-I}$	0.067*	0.005	3.976
current education, training$_I$	0.625***	0.043	1.729
number of children in household$_P$	-0.951***	-0.065	0.221
education of the mother	-0.112***	-0.008	2.416
local employment rate$_I$	-0.019***	-0.001	87.098
ρ	-0.428*		
Nobs, LogL	380	-356.414	
count actual/predicted	$\text{WFP99}_P^* = 0$	$\text{WFP99}_P^* = 1$	total
$\text{WFP99}_I^* = 0$	40/11	91/112	131/123
$\text{WFP99}_I^* = 1$	65/58	184/199	249/257
total	105/69	275/311	380/380
equal WFP actual/predicted	224/210		
unequal WFP actual/predicted	156/170		

'*','**', or '***' denote that the parameters are significantly different from zero at the 10 percent, 5 percent, or 1 percent levels, respectively.

But again, there are some observable social interactions. The peer's work force participation has a positive influence on the work force probability of the regarded younger brother or sister. This confirms the hypothesis of competition between brothers and sisters.

Like the results in the 1985 wave, increasing age has a positive impact on the work force probability. The variable sex has a negative sign, meaning that women still have a lower work force probability.

In this wave, the variable gender difference and birth order also has a negative sign. An elder sister still has a negative impact on her brother's work force probability and an elder brother a positive one on his younger sister. However, some change in comparison to the 1985 results arise in the marginal effect of the variable gender difference and birth order. In the 1999 wave, an elder sister has a weaker negative impact on her brother's work force probability. We suppose that this change is due to the change of women's role in society. On one hand, emancipation has made important progress, on the other, efforts to promote women have made an impact. Although women may still be discriminated against (and have a lower work force probability), their work force participation has become more normal. This is especially true for women in the new *Länder*. Additionally, by now it has become more normal that women first try to make their way in professional life before starting a family. They are frequently in their thirties when they get pregnant and stop working (or not).[4] The mean age of the persons interviewed, however, is between 23.8 (second-born) and 27.8 (first-born).

If both siblings live in the same household, the work force probability of the younger sibling diminishes. This is probably due to the lower cost of living in a shared household, but it also underlines risk-sharing between siblings. Apparently, distance plays a role with respect to risk-pooling. Obviously, it is less appealing to share a job risk if your brother or sister does not live in the same household.

[4] Kreyenfeld (2000) shows a pronounced increase in age for the first-birth for cohorts in West and East Germany.

As expected, a growing number of children in a household has a decreasing influence on the work force probabilty. An additional variable for the number of own kids of the female individuals is not significant. This means that it makes no differences for the job participation behavior of a woman whether her own kids or the kids of her partner live in the same household. Also the marital status or the variable living with a stable partner plays no significant rule.

The impact of differences in the school-leaving certificate has the expected sign, i.e. a lower certificate of the peer implies a lower probability of work force participation of the second born.

The net household income - as the sum of all household members including parents, spouses or partners - has a positive effect on the work force probability. But, because the own net income is not excluded in this variable, some endogeneity bias might play a role in the outcome.

If the monthly income of the first-born in the year before decreased with respect to the income of the second-born, the work force probability of the second-born increases with a time lag of one year. This implies that there is some kind of risk-sharing between both siblings with positive effects on the work force participation in bad income situations of the peer.

In the decision equation of the first born the variables own age, age gap between first- and second-born, a dummy variable for beeing currently in education or training[5], number of children, education of his or her mother and local employment rate are significant. Age and the age gap increase the work force probability of the first born, whereas the number of children decreases it.

If the education of a person's mothers is low he or she will be with higher

[5] In large data sets, the decision of being currently in education or training may be explained by a separate decision equation. Here, we include this dummy variable in the work force participation decision equation, knowing that we possibly introduce some endogeneity bias.

probability in the work force. We suppose that this result is due to a higher probability of being in the education system (and not working) if the mother has a high school certificate. The local employment rate also has a negative influence. This means that in a *Land* with a low unemployment rate the young adults can spend some time not working perhaps because it is easier to be financed from relatives.

The prediction accuracy of our bivariate probit model is quite good. In 81.05 percent all simultaneous work force participation decisions are correctly predicted. Nevertheless, some reservations remain with respect to the explanation equations for the peer. Especially the predictions given for the case of simultaneous non-participation of the siblings are unsatisfactory, although we tried many versions in the model selection process.

4 Conclusions

Monte Carlo results indicate that the power of parameter tests concerning an endogeneous dummy variable in the bivariate probit model variables is low. This is especially true if there is a medium-sized or strong residual correlation between both equations. Nevertheless, in our empirical study we find significant evidence for social interactions in the work force participation behavior. The work force participation of the elder brother or sister as well as educational and gender differences are significant and observable social influences for the labor market decision. The respective household incomes of both siblings and the question whether they are living in the same household also play an important role. The younger brother or sister compares himself or herself to the elder one, not the other way round, and takes a similar work force decision.

This confirms the view of psychometricians that birth order plays an important role in human behavior. Birth order is seen as a source of different sibling strategies in competing for parental favor and investment. The strategic variations arise because birth order is correlated with differences in age, physical size, power and status within the family (see Sulloway, 2001).

In our empirical analysis, we see that the competition motive is the dominant force of interactions between young adult siblings in the eighties, whereas in the 1999 wave, both risk-pooling behavior and competition in the work force participation decision can be proved.

References

Akerlof, G.A., 1997, Social distance and social decisions, Econometrica 65, 1005-1027.

Bikhchandani, S., Hirshleifer, D. and Welch, I., 1992, A theory of fads, fashion, custom, and cultural change as informational cascades, Journal of Political Economy 100, 992-1026.

Brock, W. and Durlauf, S.J., 2001, Discrete choice with social interactions, Review of Economic Studies 68, 235-260.

Brock, W. and Durlauf, S.J., 2002, A multinomial-choice model of neighborhood effects, American Economic Review, Papers and Proceedings 92, 298-303.

Clark, A.E. and Oswald, A.J., 1996, Satisfaction and comparison income, Journal of Public Economics 61, 359-381.

Cole, H., Mailath, G. and Postlewaite, A., 1992, Social norms, savings behavior, and growth, Journal of Political Economy 100, 1092-1125.

Corneo, G. and Jeanne, O., 1999, Segmented communication and fashionable behavior, Journal of Economic Behavior & Organization 39, 371-385.

Dercon, S. and Krishnan, P., 2000, In sickness and in health: Risk sharing within households in Rural Ethiopia, Journal of Political Economy, 108, 688-727.

Greene, W.H., 1998, Gender economics courses in liberal arts colleges: Further results, Journal of Economic Education 29, 291-300.

Gordon, D.V., Lin, Z., Osberg, L. and Phipps, S., 1994, Prediction probabilities: Inherent and sampling variability in the estimation of discrete-choice models, Oxford Bulletin of Economics and Statistics 56, 13-31.

Hayashi, F., Altonji, J. and Kotlikoff, L., 1996, Risk-sharing between and within families, Econometrica 64, 261-294.

Jaenicke, J., 2003, Bivariate probit models of social interactions: Some Monte Carlo results, Bulletin of the International Statistical Institute, Contributed Papers, 60 (1), 543-544.

Kreyenfeld, M., 2000, Changes in the timing of first birth in East Germany after re-unification, Schmollers Jahrbuch 120, 169-186.

Lollivier, S., 2001, Endogénéité d'une variable explicative dichotomique dans le cadre d'un modèle probit bivarié, Annales d'Économie et de Statistique 62, 251-269.

Maddala, G.S. and Lee, L.-F., 1976, Recursive models with qualitative endogenous variables, Annals of Economic and Social Measurement 5, 525-545.

Maddala, G.S., 1983, Limited-dependent and qualitative variables in econometrics (Cambridge University Press, Cambridge).

Manski, C.F., 1993, Identification of endogenous social effects: The reflection problem, Review of Economics Studies 60, 531-542.

Manski, C.F., 2000, Economic analysis of social interactions, Journal of Economic Perspectives 14, 115-36.

Murray, C., 2002, IQ and income ineqality in a sample of sibling pairs from advantaged family backgrounds, American Economic Review, Papers and Proceedings 92, 339-343.

Murphy, A., 1995, Female labour force participation and unemployment in Northern Ireland: Religion and family effects, Economic and Social Review 27, 67-84.

Ogaki, M. and Zhang, Q., 2001, Decreasing relative risk aversion and tests of risk sharing, Econometrica 69, 515-526.

Oreopoulos, P., 2002, Do neighbourhoods influence long-term labour market success? A comparison of adults who grew up in different public housing projects, Statistics Canada, Family and Labour Studies Division, Ottawa, Research Paper 185, http://www.statcan.ca/english/research/11F0019MIE/11F0019MIE2002185.pdf.

Solon, G., Page, M.E. and Duncan, G.J., 2000, Correlations between neighboring children in their subsequent educational attainment, Review of Economics and Statistics 82, 383-392.

Sulloway, F. J., 2001, Birth order, competition, and human behavior, in: P.S. Davies and H.R. Holcomb, eds., Conceptual challenges in evolutionary psychology: Innovative research strategies (Kluwer Academic Publishers, Dordrecht and Boston) 39-83.

Wilde, J., 2000, Identification of multiple equation probit models with endogenous dummy regressors, Economics Letters 69, 309-312.

Woittiez, I. and Kapteyn, A., 1998, Social interactions and habit formation in a model of female labour supply, Journal of Public Economics 70, 185-205.