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Policy options promoting market participation among smallholder livestock producers: a case study from the Phillipines

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Abstract

We investigate the factors precipitating market entry where smallholders make decisions about participation (a discrete choice about whether to sell quantities of products) and supply (a continuous-valued choice about how much quantity to sell) in a cross-section of smallholders in Northern Luzon, Philippines, in a model that combines basic probit and Tobit ideas, is implemented using Bayesian methods, and generates precise estimates of the inputs required in order to effect entry among the non-participants. We estimate the total amounts of (cattle, buffalo, pig and chicken) livestock input required to effect entry and compare and contrast the alternative input requirements. To the extent that our smallholder sample may be representative of a wide and broader set of circumstances, our findings shed light on offsetting impacts of conflicting factors that complicate the roles for policy in the context of expanding the density of participation.

Keywords: Policy options; Market participation; Smallholder livestock supply

In a recent study Delgado et al. (1999) report that from the beginning of the 1970s to the mid-1990s, consumption of meat and milk in the developing countries increased by 175 million metric tons, more than twice the increase that occurred in developed countries. For the year 1990 they calculate that the market value of that increase in meat and milk consumption totals approximately $US155 billion, more

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than twice the market value of increases in cereals consumption under the green revolution. They argue that population growth, urbanization and income growth—factors that fuel the increase in meat and milk consumption—are expected to continue over the next several decades creating a veritable livestock revolution. This revolution presents new and expanding market opportunities for smallholder livestock producers. Delgado et al. (1999) project that per capita consumption of meat and milk in both the developing and the developed countries will increase by about 50% from 1993 to 2020, and that developing countries—where at least three-fourths of livestock production come from smallholder, backyard producers—will supply about 60% of all meat products and 52% of all milk products. Hence, prima facie the future appears to hold enormous untapped potential for smallholder livestock producers and, in particular, opportunities to alleviate the poverty trap through devising strategies that will enable increased entry and sustained profitability from emerging livestock markets. Nevertheless, inappropriate policies and misallocation of investment resources could skew the distribution of the benefits and opportunities away from those smallholders who would potentially gain the most from this revolution. In this context, a search for policies designed to enhance benefits to smallholders seems appropriate and this is the main objective of this exercise.

Improving access to markets to benefit from the rapidly growing demand for livestock products is one option that policy-makers must consider. However its effect is complicated by the potentially offsetting effects of demography, labor mobility, opportunities for off-farm employment, and the competing impacts that physical, financial and intellectual capital accumulation may have, especially when diverse opportunities for resource allocation exist. For example, smallholders generally have inadequate capital resources—including, physical and financial resources, but also intellectual capital resources such as experience, education and extension—that limit their abilities to diversify production portfolios. When an increase in the capital stock arises, for example, through an increase in education levels, and alternative employment opportunities exist, it is unclear just what the impacts of the increased capital stock will be on both the participation and supply decisions in livestock markets. Similar arguments exist in the context of examining increases in incomes from alternative sources, such as remittances and returns to other farm activities. When alternative employment opportunities exist it is unclear just what the allocation towards the market will be.

Additional issues further complicate policy design. For example, the inability of smallholder producers to take advantage of economies of scale in production and marketing is a significant impediment to participation. Because they are better able to take advantage of scale effects, blanket policies such as price supports are often biased towards large producers because such policies often favor physically and financially capital-intensive production systems. In addition, smallholders are often disadvantaged due to poor access to information and market-precipitating services such as extension visitation and credit assistance and these impediments often give rise to low rates of adoption of improved technologies that could potentially increase productivity. In addition, poor infrastructure often increases the transactions costs of smallholder market participation. When this is the case it is an open question as to the design of appropriate policies to precipitate entry.

In short, alternative employment prospects complicate policy analysis about market participation and supply decisions and leave considerable scope for econometric inquiry. This study provides an empirical basis for identifying options to increase the participation of smallholders in livestock markets in the Philippines. Our regional focus is prompted by the availability of detailed data on demographic variables that impact household resource decisions, labor mobility and capital formation across a set of like households, some who participate in livestock production and marketing activities and some who do not. In this context we provide precise evidence on the offsetting impacts of competing factors on the joint decisions to participate in a market and furnish positive supply. One important measure for policy analysis concerns the minimum amounts of key inputs that enables entry among the non-participants, increases the density of market participation in rural areas and, thereby, overcomes one of the principal impediments to further economic development in the region of focus. We show how this quantity can be estimated as a by-product of the estimation exercise and that the estimated quantities are of vital importance in devising policy prescriptions.

Section 2 presents a simple framework for investigating market participation and supply decisions that lends itself to traditional probit and Tobit estimation. Section 3 discusses the intuition underlying the basic model and the estimation algorithm that is used in the empirical application. Section 4 introduces the empirical application and section five presents results. Conclusions are offered in Section 6.

Modelling participation and supply decisions

We consider the participation and supply decisions in the context of traditional probit and Tobit models applied to household production data. For each household, i, i = 1, 2,…N, assume that the observed data, namely $y_i = 1$ if participation is observed and $y_i = 0$ otherwise, is conditioned by a K-vector of household-specific covariates, x_i. The decision rule is to participate when the utility of doing so, say, $U_i(x_i)$ exceeds utility $V_i(x_i)$, which is the utility reaped in return for resources x_i allocated to some alternative enterprise. Taking Taylor-series expansions of these two utility functions around the point $x_i = 0$, yields the linear model, $y_i = 1$ if $x_i \gamma > x_i \mu$, $y_i = 0$ if $x_i\gamma \leq x_i \mu$, where γ and μ are K-vectors of first-order effects depicting the impacts on the two utilities of changes in the levels of the covariates. Subtracting the left-hand-side from both sides of the inequalities, equating the result to a latent variable, z_i, and permitting the equality to hold with error, u_i, we are left with

$$z_{pi} = x_i\beta_p + u_{pi}, \quad z_i > 0 \text{ if } y_i = 1, \quad z_i \leq 0, \text{ otherwise.} \tag{1}$$

Here $\beta_p \equiv \gamma - \mu$ measures the difference in allocating resources to either enterprise.[1]

[1] In the analysis we will constrain the conditional variance of this equation to equal the value one. This restriction should not be troublesome. The restriction is the conventional one imposed for identification of the probit model and pertains to both the classical (sampling-theory) view and the Bayesian approach

Supply decisions are modelled in a similar way. We assume that the quantity supplied on the market is a linear function of another set of household characteristics, which may be the same as the set represented by the covariates x_i, above. Specifically, the supply relationship is

$$z_{si} = x_i\beta_s + u_{si}, \tag{2}$$

where z_{si} denotes household i's propensity to supply; x_i denotes covariates relevant to the supply decision; β_s denotes a vector of unknown parameters depicting the relationship between supply and the household covariates; and u_{si}~$N(0,\sigma_{si})$ denotes random error.

Unlike the latent specification in the probit model, the dependent variable in (2) takes on positive and zero values. When a zero value is observed, we assume this to imply that the household in question, rather than possessing an excess of the marketable product, actually has a demand for the commodity (that is, a negative supply). Hence, sales quantities are left-censored at zero. This simple observation is developed further in Fig. 1.

Fig. 1 depicts the utility-maximizing household-supply decision. Utility (which is, of course, latent or unobservable) is depicted on the vertical axis and the potential sales quantity is depicted on the horizontal axis. For two households (households i and j) one household maximizes utility by producing a positive sales quantity (z_{sj})

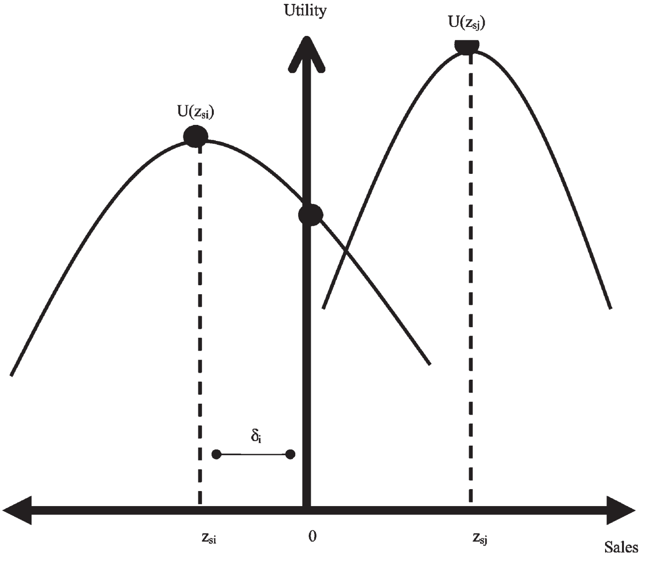

Fig. 1. Utility-maximizing sales values and distance-to-market latency.

adopted in this paper. Specifically, the error variance is constrained to equal one to overcome an identification problem arising due to the fact that the latent-variable specification in Eq. (1) is neither scale nor location independent. See, for example, Greene, 1993, p. 880.

whereas the second finds utility maximized at a negative supply quantity (z_{si}). Unlike the first household, the second household's implicit supply quantity is unobserved and latent. This latent value is very important for policy purposes because it provides a simple and highly intuitive quantity with which to measure a household's distance from market (δ_i). As such, the values δ_i, for i $\in$ (the censor set) $c \equiv \{i | z_{si} = 0\}$ are an important part of the estimation exercise. In the section that follows we outline briefly how they can be used to simplify the estimation and how these latent values can also be used importantly in policy. But one other feature of this two-equation set-up is noteworthy. The errors in the two equations are likely to be correlated. In other words, the two equations will be linked in a system with a common covariance. For future reference

$$\sum \equiv \begin{pmatrix} \sigma_{pp} & \sigma_{ps} \\ \sigma_{sp} & \sigma_{ss} \end{pmatrix}, \quad (3)$$

defines the covariance between the participation and sales equations.

Estimation

Probit developments and estimation follow Albert and Chib (1993); Tobit estimation follows (the seminal Bayesian paper on censored regression models) Chib (1992); and joint estimation of the two components evolves from combining ideas implicit in both sources. Here we present only the intuition underlying the approach and some of its key advantages and attractions for policy; mathematical details are relegated to an appendix. In each of the contributions just itemized, a key step in the procedure is to augment the probability measure (the joint posterior probability density function, or, pdf) for the unknown quantities with the latent data, which are the negative 'sales' quantities projected for each household, given its vector of observed covariates, and the knowledge that it is not participating in the market. Put another way, at each point in the data wherever a censored quantity is encountered, we insert an estimated value based on the household's resource stock and the observed fact that it is not trading. At first glance this step may seem rather counterintuitive. But the introduction of these latent or 'missing' quantities serves to circumvent some difficult estimation issues and avoid working with a fairly intractable specification of the likelihood function, a point that is well articulated in the seminal paper by Chib (1992). There the introduction of these latent quantities is purely for technical purposes and their development and motivation is given scant attention. But, as we now demonstrate, these latent quantities also have considerable appeal from a policy perspective. Precisely, these quantities can be used as indicators of a household's 'location' in relation to the market. This location or 'proximity' is not defined in physical space but, rather, is conceptualized over measures of the sales values themselves or, alternatively, over measures of the covariates (household resources or characteristics) deemed to have a significant impact on sales.

To clarify, recall Fig. 1, now with an additional non-participating household

(household ‘k’) appended. As before, household j is a participant whereas households i and now k are non-participants. In both cases, however, and despite the fact that the two non-participating households report zero sales, households i and k are, of course, quite different; they are particularly different from a policy perspective where getting households into the market is a key objective. In short, household i resides closer to the market than household k, and this fact is represented in the figure by the two distinct points z_{si} and z_{sk}, and by the two distinct distance measures δ_i and δ_k. The techniques outlined in Chib (1992), in the case of the Tobit model, and by Albert and Chib (1993), in the case of the probit model, rely specifically on the different estimates of the quantities δ_i and δ_k to make estimates of the model parameters in the system. It does this by inferring their levels given other information in the system. In essence, the quantities δ_i and δ_k are estimated as part of an iterative algorithm that updates estimates of the equation parameters given estimates of the missing data points δ_i and δ_k and, subsequently, updates estimates of δ_i and δ_k given estimates of the equation parameters. Iterating between these two blocks of unknown quantities—the equation parameters on the one hand and the missing or latent data on the other—generates a Markov chain with desirable convergence properties that yields estimates of the unknown quantities in the system. The roots of the idea are quite old (Metropolis et al., 1953; Hastings, 1970), but have only recently been exploited in the statistics literature (Gelfand and Smith, 1990), whereupon a veritable explosion of these ideas has arisen in the medical, biological and social sciences. However, we have not yet witnessed their application to problems in development economics. The application below gives some indication of their value in this context.

Turning once again to Fig. 2, market access policy typically surrounds questions related to the reasons why neither households i nor k are trading; the reason for the

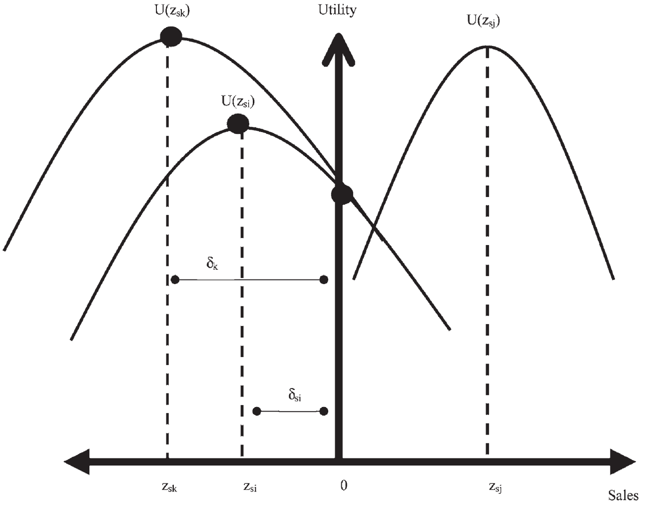

Fig. 2. Relative distance measures and latent-variable estimation.

difference between the two distances to market; and the inputs deemed necessary to make either one, or both of them enter the market. Each of these questions is at the heart of the market access debate and each is resolved—to varying degrees—in the context of the Tobit equation in the two-equation model. For any nonparticipating household, say household i, once the significant set of covariates—say x_i—has been uncovered and a corresponding latent quantity, say, z_{si}, has been estimated, the problem of determining the minimum amount of a given input required in order for the household to enter the market is simply the quantity of the input that makes the quantities δ_i and δ_k in Fig. 2 vanish. Put another way, if Eq. (2) defines the (linear) relationship between sales and household characteristics, to obtain a distance measure defined with respect to a particular covariate—say x_{ji}—we simply find the quantity of covariate j that makes the right-hand side of Eq. (2) equal zero. In other words, we locate the quantity

$$\hat{x}_{ji} = \frac{-\mathbf{x}_{i\text{-}j}\boldsymbol{\beta}_{s\text{-}j}}{\beta_{sj}}. \quad (4)$$

This expression defines the amount of resource j that is required by household i in order for it to enter the market. Here $x_{i\text{-}j}$ denotes the covariate matrix with the column corresponding to covariate j excluded; $\beta_{s\text{-}j}$ denotes the corresponding coefficient vector; and β_{sj} denotes the coefficient of covariate j in the Tobit regression. Due to the appearance of the latter coefficient in the denominator of (4), the expression on the right-hand side does not have a form that enables direct simulation. But, once again, using the Gibbs sequence we are able to generate a sample of draws for $\hat{x}_i$ and, in so doing, characterise its location and scale. These estimates are extremely important for policy purposes. Interestingly, their derivation follows simply from inserting Eq. (4) into the estimation algorithm for the combined probit–Tobit model. In short, a modest extension of some fundamental ideas in Bayesian estimation of discrete-choice and censored-regression models generates estimates of quantities that are important for policy.

Application

The model is applied to data from a crop-livestock village in the Philippines obtained from a household survey that was conducted in Don Montano, the study site of the Crop-Animal Systems Research Project (CASREN).[2] This project is aimed at generating technology and policy options to increase the productivity and economic viability of smallholder crop-animal systems in rain-fed areas. The study of policy options focuses on identifying ways to improve the market participation of smallholder livestock producers in the area.

[2] This study is one component of the project that is being funded by the Asian Development Bank under a Regional Technical Assistance (RETA) Grant.

Don Montano is one of 58 barangays[3] in the Municipality of Umingan in the province of Pangasinan, within northern Luzon—a principal island of the Philippine archipelago. It used to be a wide tract of land owned by a Spanish haciendero[4] named Don Montano Castillo, who donated part of his land to the municipality to become what is presently the barangay named after him. Don Montano is characterized by farmlands situated at the foot of the partly denuded Caraballo Mountain. It has a total land area of 297 hectares (ha), two-thirds of which is rain-fed lowland. It has a climate with distinct wet and dry seasons (wet from May to October, and dry from November to April) and sandy loam soil. There are 329 households in Don Montano consisting of a total population of 1738 persons, or an average household size of between five and six members. Ninety percent of the residents are farmers with an average land holding of 1.5 ha. The major crops grown in the area are rice, corn, onion, peanut, mung-bean, and vegetables. The animal species that are commonly raised by smallholder farmers include beef cattle, buffalo, goat, pig, and poultry.

Structured questionnaires were designed to collect primary data from a sample of smallholder livestock owners. These include both combined and separate questionnaires for producers and non-producers, a questionnaire on technology adoption, and a survey recording daily food consumption during a one-week period.[5]

A total of 110 households (consisting of 75 smallholder/backyard livestock producers and 35 non-producers) were interviewed by a team of enumerators from Central Luzon State University together with International Livestock Research Institute (ILRI) staff. The sample respondents were randomly picked from a list of households that was generated from a census to determine the sample population. The complete interview was executed in two rounds. The first round took place in April–May 2001, and the second round took place in August 2001. The survey's primary aim was to generate information on household characteristics, production, consumption, sales, transactions costs, credit, technology adoption, and perceptions about livestock production. Table 1 presents descriptive statistics partitioned by market participation status.

The combined ages of the household head and spouse is considered a priori to be a potentially significant determinant of participation status. At the least, its inclusion in similar studies necessitates inclusion in the present investigation, but perhaps younger households may have a greater predisposition towards entry because they may be at a steeper gradient on the learning curve, or because they may be more malleable and, thus, mobile in considering alternative employment opportunities. On the other hand, when alternative non-livestock-market employment opportunities exists, as they appear to do for a great majority of the sample due to their locations nearer townships, an opposing case can be argued, leading us to the conclusion that the sign of the age-variable coefficients in both the probit and Tobit equations is

[3] A barangay is the smallest political unit in the Philippines.

[4] A Spanish term for rich landed farmer.

[5] The survey forms on consumption and technology adoption were administered during the second round of data collection.

Table 1
Characteristics of livestock producers and non-producers in the study site (Barangay Don Montano, Umingan, Pangasinan, Luzon Island, Phillipines)

Characteristic	Participant (n = 75)	Non-Particpant (n = 35)
Age		
Household head	47 (13.9)	45 (17.2)
Spouse	43 (13.1)	38 (13.7)
Educational attainment		
Household head	9 (3.0)	8 (3.0)
Spouse	9 (2.5)	10 (3.3)
Gender household head (%)		
Male	71 (95)	30 (86)
Female	4 (5)	5 (14)
Household members	5 (1.73)	4 (2.09)
Available family labor (aged between 15 and 69 years old)	2.97 (1.38)	2.66 (1.33)
Main occupation (%)		
Farmer	80	26
Farm laborer	4	30
Housekeeper	3	9
Government employee	5	3
Private employee	8	20
Overseas worker	0	6
None	0	6
Household income (peso)	55 094	60 903
Percent from:	(54 628)	(91 104)
Crop production	29	3
Sale of livestock	6	0
Farm labor	3	4
Non-farm	53	76
Remittances	9	17
Household assets (peso)	33 109 (69 711)	26 874 (53 568)
Farm size (ha)	0.99 (0.88)	0.63 (0.32)

Numbers in parentheses are standard errors. Data are from the survey enacted for the project 'Policy Options for Improving the Market Participation of Smallholder Livestock Producers,' April–May, 2001.

ambiguous. Additionally, Table 1 suggests that there is no significant difference in age between the participating and non-participating sub samples.

As in the case of 'age,' we can make converse arguments for the impacts of 'educational attainment' on participation status. Table 1 suggests no significant difference between the sub-samples, but its potential impact stems from the likelihood that higher educational experience generates additions to the intellectual capital stock which may, in turn, lead to increased potential for skills acquisition during participation; but when alternative employment opportunities prevail it may be the case that these additions to the capital stock effect reallocation in paid employment and, so, the ultimate impacts remain an empirical question.

What differences there are between the two sub-samples in terms of the number of household members, the availability of family labor, and their occupations (exclusive of farming, wherein a larger proportion of participants are engaged), appear to be insignificant. Only the gender status of the household head appears to be significant, with participants originating mainly in male-headed households. Income, asset holdings, and farm size are also insignificantly distinguished in the sub-samples. Non-farm income sources appear prominently as major contributors to household income in both sub-samples, with non-participants exhibiting a larger share. These non-farm activities mostly consist of non-farm employment (professional and/or non-professional) in the nearby major urban center. Of interest, as well, is the important contribution of crop production to household income, and this figures prominently among participants more than non-participants. This is not surprising given that the study area is a predominantly rice-based farming system with livestock production as a secondary farming activity. Livestock sales contribute less than 10% on average; however, it is important to emphasize that these occur during important periods of the year when the household is in cash deficits (i.e. during the start of the annual cropping season, school openings, in times of major household expenses for medical reasons, hospitalization, weddings, festivities, and the like). This seems to suggest a symbiosis between crop and animal production activities, allowing for smoothing of income flows and providing households with a buffer against inherently risky agricultural production activities.

In summary, with the exceptions of principal occupational status and the gender status of the household head, there appear to be no readily discernible differences across sub-samples, implying that the key determinants of differences in participation status must be correctly discerned through more formal methods. In short, there exists considerable scope for empirical enquiry.

Results

Table 2 reports results of the Gibbs-sampling, data-augmentation algorithm applied to the participation and sales data. The first column of the table reports definitions. Posterior mean estimates of the parameters are reported in the body of the table, accompanied by their 95% highest posterior density regions, which are enclosed in parentheses. These intervals are obtained from the Gibbs sample and are the Bayesian analogues of the frequentist (sampling-theory) confidence intervals. The dependent variable in the Tobit equations is livestock sales revenues in thousands of Philippine pesos. The covariates are ordered in blocks corresponding, respectively, to the categories Demography, Mobility, Intellectual Capital, Financial Capital, Physical Capital, Credit and Other Excluded Covariates—a classification motivated as follows.

First, we consider that certain demographic variables have impacts on the implicit costs involved in transacting in livestock markets. A conscientious reviewer prefers that we circumvent the links between household demographic variables and an explicit transactions-costs interpretation; perhaps this is wiser than the path we follow in the remainder of the paper, but we feel that it is perhaps more useful to keep this key linkage between a classic work, a sample of Philippine smallholders and a grow-

Table 2
System, joint Probit and Tobit equation estimates of the impacts of covariates on entry and sales decisions by Philippine livestock smallholders (218 observations), Northern Luzon, 2001

		Probit			Tobit	
Demography						
Distance		−0.08			−1.71	
	(−0.39)		(0.20)	(−4.36)		(0.92)
Members		−0.42			−2.29	
	(−0.68)		(−0.18)	(−4.33)		(−0.49)
Mobility						
Otheremp		−0.02			−0.08	
	(−0.04)		(0.01)	(−0.31)		(0.15)
Intellectual capital						
Education		−0.09			−0.28	
	(−0.15)		(−0.04)	(−0.76)		(0.16)
Farmex		0.00			0.09	
	(−0.02)		(0.02)	(−0.07)		(0.25)
Otherex		−0.14			−1.65	
	(−0.45)		(0.07)	(−4.38)		(0.52)
Extension		0.58			3.31	
	(0.12)		(1.05)	(−0.33)		(7.12)
Financial capital						
Otherinc		0.01			0.09	
	(0.00)		(0.02)	(0.01)		(0.17)
Remitinc		0.01			0.11	
	(0.00)		(0.03)	(0.03)		(0.19)
Memberinc		0.01			0.07	
	(0.00)		(0.02)	(0.00)		(0.14)
Cropinc		−0.02			−0.14	
	(−0.03)		(0.00)	(−0.26)		(-0.02)
Physical capital						
Cattle		0.44			3.74	
	(0.31)		(0.58)	(2.65)		(5.02)
Buffalo		0.47			3.40	
	(0.17)		(0.77)	(1.10)		(5.84)
Goat		−0.07			−0.15	
	(−0.22)		(0.07)	(−1.24)		(0.91)
Pig		0.55			3.50	
	(0.34)		(0.80)	(2.31)		(4.92)
Chicken		0.05			0.34	
	(0.03)		(0.07)	(0.22)		(0.49)
Debt						
Credit		−0.03			−0.15	
	(−0.08)		(0.01)	(−0.53)		(0.19)
Other						
Constant		−0.21			−10.15	
	(−1.50)		(1.10)	(−22.58)		(1.27)

(*continued on next page*)

Table 2 (*continued*)

		Probit			Tobit	
Covariance						
Participation		1.00			4.11	
	(1.00)		(1.00)	(2.76)		(5.66)
Sales		4.11			91.39	
	(2.76)		(5.66)	(50.47)		(153.24)
Predictions						
Non-parts.						
Positive		13.77			12.52	
	(8.00)		(19.00)	(7.00)		(18.00)
Negative		152.23			153.48	
	(147.00)		(158.00)	(148.00)		(159.00)
Participants						
Positive		27.36			25.70	
	(21.00)		(33.00)	(19.00)		(32.00)
Negative		24.64			26.30	
	(19.00)		(31.00)	(20.00)		(33.00)

Reports in parentheses below posterior means are 95% highest-posterior density intervals.

ing recent literature on transactions-costs economics, market access and market development (see, for example, Key, Sadoulet and de Janvry (2000) and the literature cited therein). As Holloway et al. (2000) note in the context of emerging milk markets in peri-urban situations in the Ethiopian highlands, transaction costs embody all barriers to access to market participation by resource poor smallholders. They include the costs of searching for a partner with whom to exchange, screening potential trading partners to ascertain trustworthiness, bargaining with potential trading partners (and officials) to reach an agreement, transferring product, monitoring the agreement to see that its conditions are fulfilled, and enforcing the exchange agreement. Although the situation in rural Northern Luzon is perhaps dissimilar in many respects, the nature of informal transactions shares many similarities. The one key feature of these two situations (and so many others involving significant reallocations of household resources) is that these costs involve significant amounts of one key household resource that is present in every household, may be affected greatly by the introduction of a new enterprise such as market transactions, and may, indeed, be altered prohibitively as a result of a switch in status of the household. The household resource in question is time. Obviously, any variable that affects the structure and organization of the household has the ability to affect the availability and use of this key resource and, with it, the magnitude of barriers (qua transactions costs) inhibiting entry. Although it is simply a restatement of the ideas implicit in Becker's original treatise (Becker, 1965), this point is important, but it is here that a problem arises should we wish to estimate these costs explicitly. We do not seek to estimate these costs directly as, for example, Key, Sadoulet and de Janvry (2000), but prefer to keep this implicit relationship at hand as we study the responses to each of the covariates.

To the extent that transactions costs are likely to play a major role impeding entry by subsistence households into emerging markets, the problems of ensuring adequate demand, locating and negotiating a sale and transporting goods to market are anticipated to feature prominently in the household decision-making process. For these reasons and in the absence of precise information concerning the likely ranges of these costs, we use two proxies—return-time distance to market ('Distance') and household labor availability or number of household members ('Members')—as principal determinants. We assume that transactions costs increase with greater distance to market but may be reduced with increased labor abundance and the lower opportunity costs that this may imply. Consequently, for both participation and selling decisions we presume that the impacts of these two covariates are, respectively, negative and positive.

Second, because transition to the new occupation in local markets requires freeing-up other resources, we desire some measure of the extent to which households in question may be more or less mobile than others. This degree is represented by the variable 'Otheremp' which, in turn, measures the number of years that the household head devoted to non-farm employment activities in his/her current and previous occupations. In the absence of more precise information concerning employment prospects and the household's propensity to change occupations in response to these incentives, we use the covariate 'Otheremp' as a proxy for mobility. The larger the value of 'Otheremp,' the more likely the household is to participate in markets. In a separable household production model such insight would only relate directly to the labor market, but it may have implications in non-separable settings. For example, the variable may have implications for livestock markets where labor allocation to off-farm activities is being constrained by livestock production. Having said this, we do not have strong a priori expectations about the effect of 'Otheremp' on sales.[6,7]

Third, we assume that the level of intellectual capital stock in the household is positively related to the participation decision. However, this stock level may be related in a contradictory fashion when other employment activities are available, particularly when those employment opportunities require skill. In this way, a greater degree of intellectual capital—measured in terms of the number of years of formal schooling by both the household head and the spouse ('Education'), the number of years of experience in farming ('Farmex'), farm experience by other household members ('Otherex') and exposure to extension agents ('Extension' is 1 if the household

[6] As we demonstrated in the introduction to the application, across the sample, livestock sales are a secondary source of income, providing important seasonal or occasional cash injections. As noted by a reviewer, this observation may appear at odds with the reasoning that households are expected to give up other activities to get into livestock marketing. As the reviewer notes, perhaps at most they will give up a day here or there in order to go to market. Although this may have occurred anyway as consumers, the conjecture that a substitution between these activities arises requires testing and remains an open question for future research.

[7] Also noted by a reviewer, "household labour availability could affect livestock marketing via a number of routes, not just through lowering the opportunity cost of acquiring information etc. It could, for example, be the case that crop production is more labour intensive than livestock production; thus, households with extra labour are able to dedicate themselves more to producing crops for market".

had contact with an extension agent, is 0 otherwise)—may each exert a positive impact on the participation and selling decisions, although the precise impact of the non-farm specialist covariates ('Education' in particular) are complicated by their opportunity costs in alternative enterprises. For this reason, unlike the farm-specific variables 'Experience' and 'Extension', we do not have strong prior beliefs about the likely sign of the coefficient of 'Education.'

Fourth, we include measures of income derived from both farm and non-farm sources. The definitions of the variables are, respectively, income (100 000 pesos) from sources other than farming ('Otherinc'), income from remittances ('Remitinc'), income from other household members ('Memberinc') and income from crops ('Cropinc'). Where the income relates to livestock enterprises we consider that this has a positive impact on participation and selling, but where the income relates to other farm activities and to other non-farm activities we consider that the impact will be negative. In the case of income earned by other household members, we assume that this diversification may lead to risk reduction in household decision-making and, with it, increased propensity to undertake higher-risk activities, notably selling livestock. While this phenomenon may also suggest that returns from crop income may be positive, this sign is compounded by the fact that increased revenues from crop production may signal incentives to re-allocate away from livestock production and selling activities.

A more distinct, less diffuse set of prior beliefs are maintained with respect to the physical capital variables representing numbers of relevant livestock on the farm ('Cattle', 'Buffalo', 'Goat', 'Chicken' and 'Pig'). Each is expected to exert a positive impact on both the likelihood that participation will occur and the amount of selling that will be undertaken once the decision to participate has been made.

In the remaining category of 'Debt', we expect the covariate 'Credit' (representing the amount of indebtedness in 100 000 pesos) to have ambiguous impacts on the participation and selling decisions. This is because debt can be interpreted in two ways. The first way pertains to the fact that increased debt in other activities may lead to lack of free collateral in order to secure loans for market selling activities. In this case the sign of the coefficient of 'Credit' is expected to be negative. In the second case, existing debt may be the result of previous borrowing that has occurred for the production and selling decisions and may, therefore signal greater propensity to sell. In this case we expect the coefficient of 'Credit' to be positive.

Finally, we have no reason to expect the impacts of other excluded factors ('Constant') to be positive or negative.

Regarding the reports in the probit and Tobit equations, two observations are apparent and important. With the exceptions of a few covariates, the participation and selling decisions are mostly affected by the same factors. Second, there is very strong evidence that the errors in the two equations are positively correlated. This observation is important because it suggests that it is most appropriate to consider the participation and selling decisions simultaneously. Hence, policy recommendations concerning market access, provision of infrastructure and estimates of minimum resource levels required to effect entry should be based on this two-equation formulation.

Regarding the impacts of the various covariates on participation, numbers of household members ('Members'), education levels of the head and spouse ('Education'), extension visitation ('Extension'), and the livestock assets ('Cattle', 'Buffalo', 'Pigs' and 'Chicken') are each highly significant. Each of the coefficient estimates of these factors have marginal significance levels in excess of 5% (that is, the ninety-five percentile Bayesian highest posterior density regions corresponding to these coefficients do not contain zero). Propensity to participate declines with numbers of household members, with education and with income from cropping, but increases with respect to increases in each of the other covariates. Distance to market ('Distance'), mobility ('Otheremp'), experience in farming and other employment ('Farmex' and 'Otherex', respectively), indebtedness ('Credit') and goat livestock numbers ('Goat') are not significant determinants of participation. There is marginal significance of some of the income variables. Income from other sources ('Otherinc'), income from remittances ('Remitinc') and income from other household members ('Memberinc') have a positive influence on the participation decision, whereas increased crop revenues ('Cropinc') lowers the likelihood of livestock-market participation. These results conform to prior expectations that income diversity lowers risk and, with it, the likelihood that (potentially risky) market development will occur, and that improved alternative production and marketing opportunities in other farm enterprises such as cropping may weaken participation incentives. However, perhaps the most interesting result is the strong negative impact that education exerts on the participation decision. When alternative employment opportunities exist (as for example, employment in a non-farm profession), an increase in skills effected by increased education lowers the likelihood that market participation arises.

This last observation is confirmed somewhat by examining the impacts of education on sales in the Tobit equation. The effect of increased education on sales is insignificant. Among the remaining covariates, all have the same signs of effects as those in the probit equation. However, the marginal significance levels are significantly lower than in the probit specification. This difference is most dramatic with respect to the extension covariate. Whereas in the probit equation this covariate is highly significant, in the Tobit equation it is not. Hence, extension activities by themselves appear to play an important role, but only in the set-up of market operations. Finally, most of the remaining covariates share significance levels that are similar to those in the probit model and, once again, indebtedness, farm experience and mobility do not appear to be significant factors explaining supply decisions.[8]

The estimates pertaining to the covariance matrix in the lower portion of the table confirms our initial conjecture that the participation and sales decisions are strongly positively correlated. This fact is supported by the cross-equation error covariance reported in the lower part of the table. The implied 95% highest posterior density interval suggests that the covariance is not close to zero. Put another way, the probit

[8] As a reviewer notes: "This has to be more fundamental than entering into a complex process of ascertaining least-cost combinations of livestock holdings to maximize market participation … smallholders may have many valid reasons for holding livestock, other than for sale".

and Tobit equations estimates are not independent and should be estimated as a system.

Market entry and minimum inputs requirements

We now turn to the problem of producing estimates of the minimum levels of inputs that are required for entry among the non-participating households. This is important for gauging potential policy prescriptions to effect increased market entry. We focus on the livestock inputs (Cattle, Buffalo, Pig and Chicken) for four reasons. First, as indicated by their highest posterior density intervals, they are essential for entry into livestock markets; second, each input has a significant impact on sales that is of the 'correct' sign (positive); third, significant inter-household differences in prescribed levels of these inputs deserve emphasis; and, fourth, space limitations restrict choice to some subset of the covariates.

In reporting distance-to-market estimates, two options are available. One option is to report the additional amounts of the resources that are required for participation and the other option is to report the total amounts that are required. It is the total amounts that are referred to in Eq. (4) and in the figures that follow. Although it is argued by a referee that the total amounts might be more relevant for policy, by subtracting the actual resource levels contained in the covariate matrix the additional amounts are just as easy to obtain.

Because we treat each observation in the data set as independent and identically distributed and do not take account of the panel nature of the data, this amounts to providing reports of estimates of distance at each censored observation. There are 166 such censored observations and each of Figs. 4 to 7 reports amounts for each of the households.

Although the exact levels of the resource requirements are precisely defined in Eq. (4), a graphical motivation may prove useful. Fig. 3 presents a simplification of the linear Tobit model. The figure depicts the relationship between marketable surplus (vertical axis) and a single covariate (horizontal axis), holding constant each of the other covariates in the model. Point 'C' in the figure denotes the intersection of the predicted Tobit regression line with the origin in the marketable surplus plane and, thus, delimits the total amount of the household resource that is required for entry. Given these quantities, household 'i' is deficient by amount BC and household 'j' has an excess of the resource in the amount 'CD.' But the total distance to market of the two households is the same, at quantity AC. This distance is the quantity that is reported in each of the figures that follow. Across each household the distances will be different due to the fact that each of the households possesses different amounts of the other household resources, and these other resources also play a role in propensity to participate.

Fig. 4 presents the requirements estimates for cattle inputs across the 166 non-participants in the 218-observation sample. The estimates have been sorted (ranked) in ascending order (households that are closest to the market (such as household i in Fig. 2) are toward the left and households that are farther from the market (such as

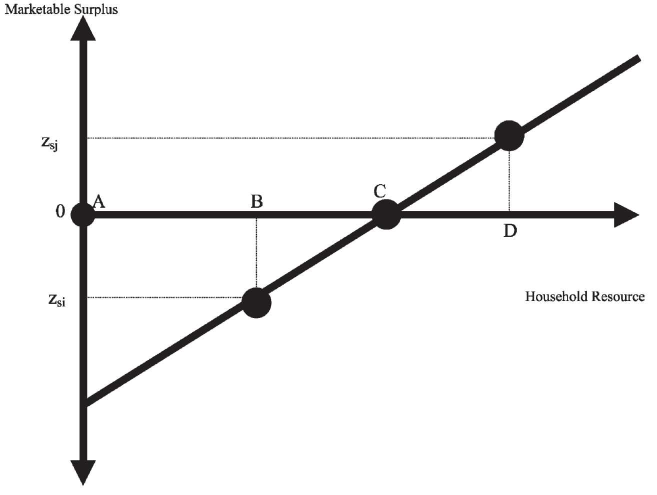

Fig. 3. Deriving distance measures from Tobit regression. Household 'i' is a non-participant whereas household 'j' participates. Line segment AC denotes the total amount required by both households, that is, their total distances to market. Because household i does not participate, its net requirement is the positive amount BC and because household j participates its requirement is the negative amount CD. The empirical distances reported in the figures that follow are the distances AC.

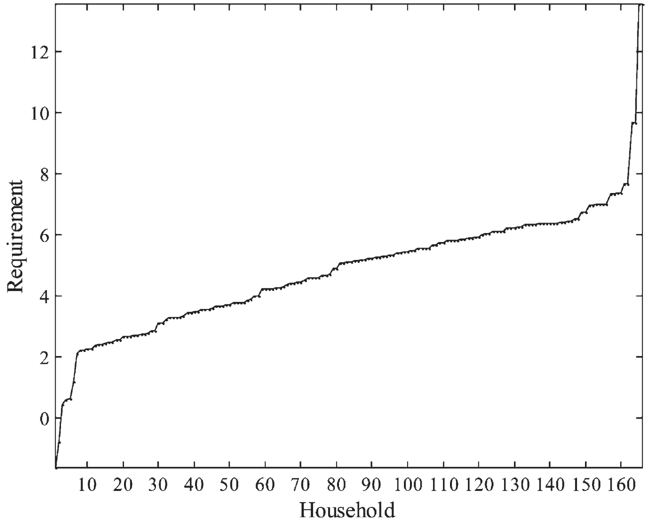

Fig. 4. Cattle inputs required for market entry.

household k in Fig. 2) are on the right). Because the distance estimates are themselves functions of random variables derived as part of Tobit regression, the distance measures have a mean and variance and, in fact, a probability density associated with each of the point estimates. The shape of the line in Fig. 4 depicts a particular

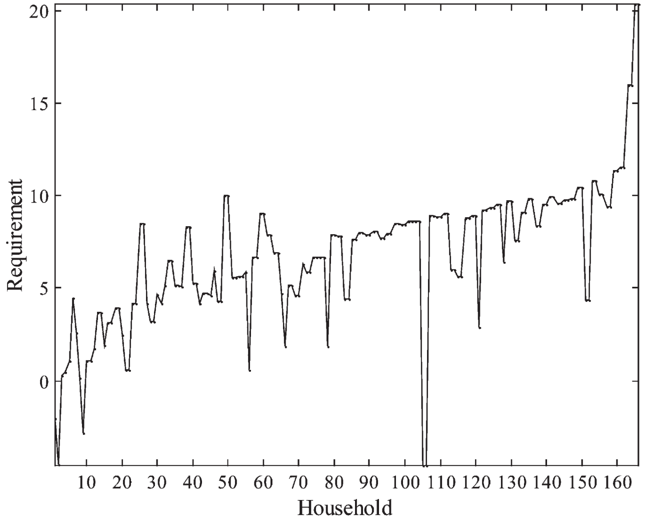

Fig. 5. Buffalo inputs required for market entry (with households ranked as in Fig. 4).

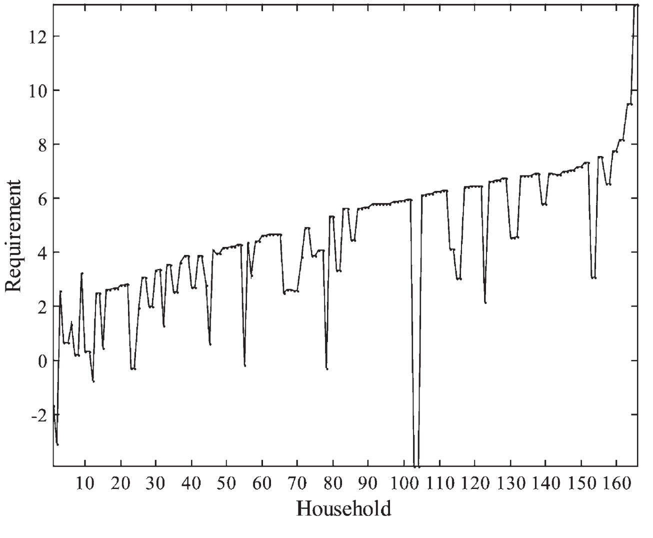

Fig. 6. Pig inputs required for market entry (with households ranked as in Fig. 4).

location and scale for the underlying distribution and coincides with a mean requirement across the 166 households of 4.79 and a standard deviation of 1.84. Average (standard deviation) holdings of cattle across the non-participating sub-sample are 0.75 (1.43) head per household compared with 2.3 (2.2) head per household in the participating sub-sample. Hence, even for the participating sub-sample, the increases over average holding are significant.

Fig. 4 serves to motivate the way in which the results from Tobit estimation can

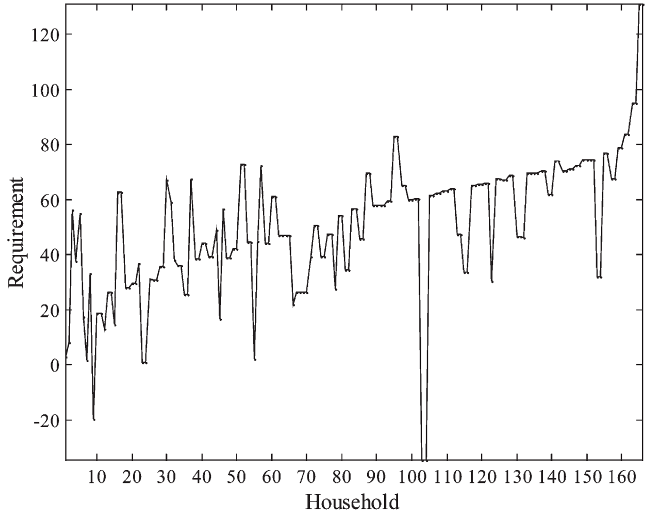

Fig. 7. Chicken inputs required for market entry (with households ranked as in Fig. 4).

be used to make recommendations about households given their characteristics, and serves to motivate further that policy recommendations will be different. This suggests that while blanket development policies like cattle dispersal for example, may be an obvious and desirable strategy, this may not guarantee the expected outcome. On the contrary, more targeted options including a whole gamut of extension programs that are tailored to fit the requirements and characteristics of the area (including its farming systems) may provide a much better likelihood of success. Further, because the equation estimates themselves are probabilistic and have associated probability distributions, the inputs requirements estimates also have associated probability distributions. In other words, the policy prescriptions themselves are random and account fully for the randomness inherent in household data sets. As noted by a referee, because the households are inherently different, a 'one-size-fits-all' policy prescription is only likely to have limited success.

In Fig. 4 the total amounts that are required for entry are sorted in ascending order. But now a question arises with respect to the rankings obtained across the remaining covariates. In particular, we question the extent to which this ranking is homogeneous or heterogeneous across the households. If the ranking is not the same it suggests that a given household may require a large number of one input before it sells, but potentially far fewer of another input. In this case, targeting particular households with particular prescriptions rather than blanket recommendations is important.

To investigate this feature of the results we present in Figs. 5–7 reports of the requirements for buffalo, pigs and chicken inputs keeping the cattle-requirements ranking constant. On average, a household will require about 5.14 head of buffalo with a standard deviation of 2.59 to effect market entry. Alternatively, the mean requirement for pigs is 4.48 head with a standard deviation of 2.62, and for chicken, is 50.49 head with a standard deviation of 24.30. The key observation is that the requirements across the households are not monotonic. In other words, a household that has a larger requirement of cattle may have a lesser requirement of buffalo, pigs and/or chickens. In some cases these differences are large. In particular, we observe at least six ‘outliers’ (violations of monotonicity) in the buffalo rankings, and observe many in the case of pigs and chickens. This finding again highlights the heterogeneity of requirements arising from differences in circumstances at the household level. In short, the patterns of inputs requirements across households and across different inputs are not the same and warrant closer scrutiny. As a reviewer notes, the finding takes us back into the role of (different forms of) livestock within the livelihood systems of different households. It suggests one avenue for extending the current effort.

Conclusions

There is strong potential for growth in livestock production and consumption in many developing countries, as indicated by recent global trends in the livestock sector (Delgado et al., 1999). This study has examined the competing effects of transactions costs, labor mobility, (intellectual, financial, and physical) capital formation and indebtedness on smallholders’ market participation and selling decisions. The important role for policy in providing an enabling environment for improving the productivity of smallholder livestock production systems is suggested by the strong effect of animal numbers in the participation and selling decisions of farmers. Technology and policy options that will enhance incentives to increase production will have a large, though indirect, impact on motivating market participation. Such options will provide a strong push to help mitigate the considerable input requirements for entry that appear to be a major stumbling block for many smallholders to become market participants. It will be worthwhile exploring in future empirical work what optimal combinations of these inputs will prove to be cost-effective and provide an answer to the inevitable research question of identifying the constraints to households holding more than they do.

Social prescriptions that increase education will, however, divert smallholder attentions elsewhere and this finding appears to be in marked contrast to other studies (for example Holloway et al., 2000) that find a strong participatory impact from education. Whether this difference stems from externalities arising from differences in off-farm employment opportunities; differences in risks associated with different commodities; or, perhaps, climatic variability, remains an open research question. In addition, potentially important insights for policy appear possible in comparison of results at different locations. For example, such comparisons may uncover additional factors explaining differences in results attributable to infrastructure, especially the quality of roads, communication and transport systems. Presently we find that ‘Distance’ (that is, the return time to transport goods to market) is not a significant determinant of participation or sales. However, the companion transactions-costs proxy ‘Members’ (the total number of members of the household) appears to significantly affect both the participation and sales decisions. We suggest that this impact may be due to increased responsibilities for risk bearing (arising from the greater flexibility to diversify) which larger household numbers engender.

The availability of alternative occupation opportunities affects significantly the potency of social and economic prescriptions and policymakers need to be mindful of these results when targeting objectives for smallholders. In addition, the emergence of capital stock variables, especially remittances, as a positive influence on market participation suggests the importance of financial security in enabling smallholders to cope with risks as well as meeting their subsistence requirements. This also points to the more important and general issue of farmers' capacities to bear risks as a critical determinant of market entry, and how this can be addressed through appropriate policy interventions that facilitate risk-bearing. Improving farm-specific skills through extension visitation appears important in precipitating entry, but not supply. Here, animal productivity-improving technologies appear to be, perhaps, the most lucrative of all policies.

Acknowledgements

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We are also grateful to Mohammad Jabbar, for comments during the conceptualization of this project; Chris Barrett, for offering numerous insights about analysis; Christopher Delgado, for useful discussions about policy issues and Alvaro Calara for assistance with the survey and data collation. Funds for this project were furnished in part by the Asian Development Bank (ADB) through the RETA 5812 granted to ILRI. Finally, two anonymous reviewers provided detailed comments that significantly improved upon our initial draft; we are very grateful to them.

Appendix. [9]

Bayesian implementation of the joint system of parameters derived from combining the probit- and Tobit equations follows from ideas in Zellner (1971); Chib (1992), and Albert and Chib (1993). Two issues that arise in combining probit and Tobit

[9] We are very grateful to one referee for providing detailed input in the presentation of the econometric details.

equations in a single system deserve particular attention. First, modifications in addition to those employed in the traditional probit model must be dealt with and, second, the specification of a non-informative prior probability distribution merits discussion.

Some of the identification issues arising here are quite similar to the ones encountered in Bayesian estimation of the multinomial probit model. They are discussed at length in McCulloch and Rossi (1994) and in McCulloch and Rossi (1996). But the system estimated here is slightly different due to the appearance of observed data in one of the endogenous variables.

Identification problems arise in the probit model due to the fact that the relationship between the dependent and the independent variables in the latent regression underlying the observed data is identified only up to a positive linear transformation. In other words, the data are just as likely to have been generated by a set of latent variables that are κ-times as large where κ is an arbitrary positive constant. The conventional procedure for handling this problem as outlined in standard texts such as Greene (1993, p. 669), is to estimate the model conditional on the restriction that the error variance is one. Albert and Chib (1993) also apply this procedure during Bayesian implementation of the single-equation Probit model. In the multivariate setting where the probit and Tobit equations are linked through a common covariance, a number of alternative options arise for imposing identification restrictions on the parameters in the context of Gibbs sampling with an informative prior. Usually, such information will not be available a priori and this situation arises in our specific application. Hence, in the estimation that follows we apply the alternative strategy of obtaining estimates conditionally on the restriction that the variance in the Probit equation is exactly equal to one. In other words, in terms of the covariance in text Eq. (3),

$$\sum \equiv \begin{pmatrix} \sigma_{pp} & \sigma_{ps} \\ \sigma_{sp} & \sigma_{ss} \end{pmatrix}, \tag{A1}$$

we estimate the model with the restriction $\sigma_{pp} = 1$ imposed. This practice is the natural and direct extension of the traditional approach to identification in the single-equation model. However, it is important to keep this aspect of the estimation in mind as we proceed.

Because this restriction is one that arises from a problem of identification and not from any prior information per se, we develop the model in the non-informative setting and discuss the identification restriction subsequently.

Data on entry and sales decisions are assumed to be generated from the latent multivariate system

$$Z = XB + U, \tag{A2}$$

where $Z \equiv (z_p, z_s)$, $z_p \equiv (z_{p1}, z_{p2}, .., z_{pN})'$ denotes the latent variables corresponding to the participation decision and $z_s \equiv (z_{s1}, z_{s2}, .., z_{sN})'$ denote the sales data augmented by the latent components z_{si}, $i \in c$; $X \equiv (x_{1'}, x_{2'}, .., x_{N'})'$, $x_1 \equiv (x_{11}, x_{12}, .., x_{K1})$, $x_2 \equiv (x_{21}, x_{22}, .., x_{2K})$, .., $x_N \equiv (x_{N1}, x_{N2}, .., x_{NK})$ denote the covariates; $B \equiv (\beta_p, \beta_s)$,

$\beta_p \equiv (\beta_{p1}, \beta_{p2}, .., \beta_{pK})'$ and $\beta_s \equiv (\beta_{s1}, \beta_{s2}, .., \beta_{sK})'$ denote the regression coefficients; and $U \equiv (u_p, u_s)$, $u_p \equiv (u_{p1}, u_{p2}, .., u_{pN})'$, $u_s \equiv (u_{s1}, u_{s2}, .., u_{sN})'$ denotes random error which, we assume, is multivariate normal with mean 0_N and covariance $\Sigma \otimes I_N$.

In the data generating model, (A2), some components of Z, namely z_{si}, $i \notin c$ are observed data and others, z_{si}, $i \in c$; z_{pi}, $i \in c$; and z_{pi}, $i \notin c$ are latent. Nevertheless, it will prove convenient to continue to use the symbol Z, noting that it contains observed components $y_{si} = z_{si}$, $i \notin c$.

We use Y to denote the $N \times M$ matrix of observed data consisting of the two N-vectors y_p, a vector of binary values indicating participation status, and y_s containing the censored supply data.

Given a prior for the equation parameters $\pi(B, \Sigma)$ we can derive the likelihood for the complete data and derive the form of the joint posterior for the unknown quantities $\pi(B, \Sigma, Z|Y)$. For this purpose, we apply the standard non-informative prior (Jeffreys, 1961)

$$\pi(B,\Sigma) \propto |\Sigma|^{-(M+1)/2}, \tag{A3}$$

which is specified in Zellner (1971, equation (8.9), p. 225). The likelihood including the missing components of Z is in the form (Gelman et al., 1995)

$$\ell(B,\Sigma,Z|Y) \propto |\Sigma|^{-N/2} \exp\{-\frac{1}{2} \text{trace } (Z-XB)'(Z-XB)\Sigma^{-1}\}, \tag{A4}$$

and the posterior is derived by combining the prior in (A3) with the likelihood in (A4) into the form

$$\pi(B,\Sigma,Z|Y) \propto \Big| \Sigma|^{-(N+M+1)/2} \exp\{-\frac{1}{2} \text{trace } (Z-XB)' (Z-XB)\Sigma^{-1}\}. \tag{A5}$$

Following Zellner (1971) and particularly standard procedures for the multivariate model (pp. 225–227), the multivariate normal pdf (pp. 379–383) and the inverse-Wishart distribution (pp. 395–396), the fully conditional distribution for the regression parameters has the matrix-normal form

$$\pi(B|\Sigma,Z,Y) \propto \exp\{-\frac{1}{2} \text{trace} \Sigma^{-1} (B-EB)'(X'X)^{-1}(B-EB)\}, \tag{A6}$$

where $EB \equiv (X'X)^{-1}X'Z$ (Drèze and Richard, 1983); that the distribution for the covariance has the inverse-Wishart form

$$\pi(\Sigma|B,Z,Y) \propto |\Sigma|^{-\nu/2} \exp\{-\frac{1}{2} \text{trace } W\Sigma^{-1}\}, \tag{A7}$$

where $\nu \equiv N+M+1$ and $W \equiv (Z-XB)' (Z-XB)$; and that the distribution for the latent data Z is in the matrix-normal form

$$\pi(Z|B,\Sigma,Z,Y) \propto \exp\{-\frac{1}{2} \text{trace } (Z-XB)' (Z-XB)\Sigma^{-1}\}. \tag{A8}$$

It should be noted that N is the length of the Z matrix and M denotes its width. Note that each of these three distributions is easy to draw samples from. Algorithms for sampling from multivariate-normal distributions are embedded in most computer packages. Draws from the inverse-Wishart distribution are readily obtained following steps outlined in Zellner (1971, pp. 389 and 395). Accordingly, the full set of conditional distributions can be simulated as part of a data-augmented, Gibbs-sampling algorithm that draws sequentially from the three matrix blocks B, Σ and Z. The steps required to do so are as follows.

Step 1: Select starting values $B^{(s)}$ and $Z^{(s)}$. Step 2: Draw $\Sigma^{(s)}$, from the inverse - Wishart distribution in (A7), conditioned by the values $Z^{(s)}$ and $B^{(s)}$ in step 1, above. Step 3: Draw $B^{(s+1)}$ from the matrix - normal distribution in (A6), conditioned by the draw for $\Sigma^{(s)}$ from step 2 and the starting value $Z^{(s)}$ in step 1. Step 4: Draw $Z^{(s+1)}$ from the matrix - normal distribution in (A8), conditioned by the draw for $B^{(s+1)}$ in step 3 and the draw for $\Sigma^{(s)}$ from step 2.

Step 5: Repeat steps 1 - 4 for a "burn - in phase" until convergence is attained.

Step 6: Repeat steps 1 - 4 and collect samples $\{B^{(s)}s = 1,2,..S\}$, $\{\Sigma^{(s)}s = 1,2,..,S\}$ and $\{Z^{(s)}s = 1,2,..,S\}$.

With reference to (A1), the identification restriction $\sigma_{pp} = 1$ is imposed by dividing between Step 2 and Step 3 each element in $\Sigma^{(s)}$ by the element ${\sigma_{pp}}^{(s)}$.

With reference to the draws for the latent data in Step 4, we exploit the fact that the observations i = 1, 2,..,N are independent. This allows us to focus on the individual rows in the matrix Z. Each row has typical element $z_i \equiv (z_{pi}, z_{si})$, i = 1,2,..,N; and it follows that the vector z_i has a multivariate normal distribution with mean vector x_{iB} and covariance matrix Σ, as defined in (A1). Consequently, using results on deriving conditional distributions from the multivariate normal distribution in Zellner (1971, pp. 381–382), the conditional mean and variance of z_{pi} are, respectively $Ez_{pi} \equiv x_{\beta p} + \Sigma_{ps}\, \Sigma_{ss}^{-1}\, (z_{si} - x_{\beta s})$ and $Vz_{pi} \equiv \Sigma_{pp} - \Sigma_{ps}\, {\Sigma_{ss}}^{-1} \Sigma_{sp}$; and the mean and variance of z_{si} are, respectively, $Ez_{si} \equiv x_{\beta s} + \Sigma_{sp}\, \Sigma_{pp}^{-1}\, (z_{pi} - x_{\beta p})$ and $Vz_{si} \equiv \Sigma_{ss} - \Sigma_{sp}\, \Sigma_{pp}^{-1}$. To obtain draws subject to the left censoring restrictions[10] $z_{pi} \le 0$ and $z_{si} \le 0$ for $i \in c$ and the right-censoring restriction $z_{pi} > 0$ for $i \notin c$, we invert a draw from the uniform distribution using the probability integral transform (Mood et al., 1974).

The procedures are implemented on a DELL™ workstation running a Pentium™ IV processor at 2.0 gigahertz with 256 megabytes of RAM and commands executed in MATLAB™ version 5.1.0.421. All computer code is available upon request. Using a burn-in phase of 1000 iterations followed by a collection phase of 5000 iterations, the algorithm took approximately 6 minutes of real time to complete.

[10] Left censoring, as opposed to right censoring, refers to a probability distribution, or a sample distribution, that has elements that are censored below a minimum level which, in this case is zero. Right censoring refers to a situation in which the distribution is censored above a maximum value. One frequent example of right censoring occurs in duration trials where, for some observations in the sample, time to failure is censored by the duration of the trial.

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