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Identifying the Poor for Efficient Targeting: Results for Papua New Guinea

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Many countries try to protect their poor during structural adjustment. Targeting is needed to prevent benefits leaking to the non-poor but screening for direct transfers may be too costly for developing countries. One solution is indirect targeting, based on the characteristics of the poor. Household survey data for urban areas of Papua New Guinea are used to show how a poverty index and probit estimation can identify multiple characteristics of poor households. The results suggest that interventions should be targeted towards larger households, where the head is unemployed and has lower levels of schooling. Female headship and age are not useful characteristics for targeting.

1. Introduction

Many poor countries, and some rich ones including New Zealand, have undergone "structural adjustment" during the last 15 years. Adjustment has taken a variety of forms but one common element is that there are significant transitional costs, and the transition takes longer than initially expected (World Bank, 1994). Countries beginning a structural adjustment now know that they face considerable short-term pain before any long-term gains occur. This raises a problem for public policy of how to protect the poor and vulnerable during structural adjustment. This is a concern not just for the country involved but also for donors and multilateral institutions, who may have pressured the country into adopting the reforms. There is not just intrinsic concern for the poor; the risk of policy reversal can be greater if sudden, sharp increases in poverty occur during the reforms.

This paper shows how household survey data can be used to identify the characteristics of poor households and help target interventions to protect the poor during adjustment. The case presented is for Papua New Guinea, which has recently begun a World Bank-led structural adjustment programme. This programme began in 1995 with cuts in government spending, tightened monetary

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policy, a floating of the currency, the introduction of user-fees for public services and the redirection of public spending towards rural areas. The initial result was that real GDP and formal sector employment fell by five percent, while the inflation rate rose from three percent in 1994 to 19 percent in 1995. Following public criticism of the adjustment programme, the government allocated K15 million for poverty alleviation in the 1997 budget.[1] The aim of this paper is to show which characteristics of households should be used if this poverty alleviation fund (and other future interventions) is to be well-targeted toward the poor.

The current study makes two contributions. It adds to the slender body of literature on the micro-economy of households in Papua New Guinea. The last published household survey was carried out in 1975 (Bureau of Statistics, 1977) and a limited amount of case study research was carried out in the 1980s (Morauta, 1984). The current data are more recent and more comprehensive because an existing but unprocessed household survey from the late 1980s was analysed for the first time as part of the research underlying this paper. This survey only covered urban households (one-sixth of the population), but this restriction may not be too serious because the main effects of structural adjustment - higher prices, reduced employment, and increased charges for public services - are likely to be felt more by urban households than by rural households. Rural households are less vulnerable because they produce their own food (landlessness is almost unknown), are not dependent upon employment income, and already lacked access to government services.

The second contribution of the paper is that it is one of the few international studies to use a multivariate analysis of the factors associated with being poor. A decomposition approach has more usually been applied (e.g., Grootaert, 1994), which, like most forms of cross-tabulation, is restricted in the number of dimensions that can be varied at one time (e.g., poverty rates broken down by region of residence and economic activity of the household head). In this paper I use a poverty index and limited dependent variable methods to identify multiple characteristics of poor urban households.

The next section of the paper examines the information requirements for targeting interventions. The presentation of the case study begins in Section 3 where the household survey data and the methods used in the analysis are described. In the next section the main findings on the regional and socio-economic correlates of poverty are presented. Section 5 offers some lessons and policy suggestions.

[1] K1=NZ$1.07.

2. Requirements for Efficient Targeting

Successful and financially feasible interventions to reduce the impact of structural adjustment on the poor require targeting to prevent leakages of benefits to the non-poor. The form targeting takes depends on the ability of governments to identify the vulnerable poor. If the poor can be identified on a household or individual level, transfer payments or some other form of direct assistance can reduce their vulnerability to adjustment. This has been termed "direct targeting" (Glewwe and de Tray, 1987). An example of direct targeting was practised in New Zealand, with increased direct transfer payments under the Family Assistance benefit mitigating the regressive effects of introducing the Goods and Services Tax. An example practised in some developing countries is supplementary feeding for people who display clear signs of malnutrition or for individuals with visibly special needs, such as lactating women.

A serious problem with direct targeting is that screening to identify the poor is costly. It requires an extensive information gathering and verification administration, which is usually provided by the state although in some cases by churches and other non-governmental organisations. Because direct targeting involves distributing benefits to some people but not to others it requires personnel who can resist the temptations of corruption. Unfortunately these conditions are not often present in developing countries and extra expenditures to create the necessary administrative capacity for direct targeting are unlikely under the conditions of a structural adjustment. If less costly shortcut methods are used the screen is often too porous, in which case many non-poor households may receive benefits. For example, self-reported income was used to determine eligibility for food rations in Sri Lanka, with the result that three times the number of households estimated to be eligible received rations (Freeman, 1981).

If providing assistance directly to the poor is not feasible, intervening on the basis of the characteristics of the poor may be required. This has been termed "characteristic targeting" (Glewwe and de Tray, 1987). This can be considered as a form of statistical discrimination where lack of information causes programme providers to use average characteristics to target intended beneficiaries.[2] For example, if the vulnerable poor consume large amounts of certain food items that are rarely consumed by wealthier households, the use of subsidies to lower the price of such items could protect the vulnerable poor with little leakage to better-off households.[3] If the poor are highly concentrated in certain regions or districts, the provision of public services to those areas could be increased. Or, if poor people are found predominantly in large households, school fees subsidies could be

[2] Statistical discrimination uses ascribed personal characteristics to provide information, relevant to an exchange, which is costly to obtain by other means (Muser, 1987).

[3] The price of cassava is subsidised in Indonesia on this basis (Timmer, Falcon and Pearson, 1983).

introduced where, for example, a family with three children in the same school did not have to pay fees for the third child.

The administrative costs of characteristic targeting are much lower than the costs of direct targeting because there is no need to assess the eligibility of each individual person or household. Leakages will be minimised if it is costly for the non-poor, in either financial or welfare terms, to adopt the characteristics of the poor just to become eligible for the intervention. This means that the substitution possibilities for the targeted characteristics should not be too elastic, which can be tested for, at least with subsidies on goods.

Finally, interventions to protect the poor must be designed so that they do not create incentives for individual choices that contribute to poverty or cause overly inefficient resource allocations. The "poverty trap" problem should not matter if the interventions are designed to only apply as transitional measures. For example, if subsidies are targeted on the basis of household size, people are less likely to have extra children if they know the intervention is only going to last four or five years. The efficiency problem is likely to depend on the size of government expenditures required for the interventions and the degree of existing distortions in the economy.

3. Data and Methods

The case study results below are derived from the Papua New Guinea Urban Household Survey (UHS), which was carried out in the late 1980s. Funding difficulties restricted the survey to just six out of the ten provinces planned, and also delayed surveying in two provinces. Nevertheless, the sample of 1093 households is a valuable source of information because: (i) the sampling frame was relatively recent (the 1980 Census), (ii) the sampling of households was staggered over the year in each town to remove seasonal effects, and (iii) the data were collected with personal income and expenditure diaries, rather than by the less accurate recall method. In addition to income and expenditures, the personal diaries also collected data on the value of own-production, gifts given and received of goods, services and money, and the value of informal sector sales. Household stocks of major food items were also measured at the start and end of the survey period. These various modules of the personal diaries allow consumption values and quantities to be derived from net purchases, own-production, net gifts, and stock changes.

The Welfare Indicator

The UHS data provide a choice between income and expenditure as a measure for the standard of living. In developing countries, expenditure data are usually considered closer to the concept of permanent income because expenditures tend to be less subject to short-term fluctuations (Anand and Harris, 1994). Income data can overstate the degree of inequality and poverty, and therefore the need for public intervention, because a wide variety of informal and voluntary transfer mechanisms operate to share income amongst households.[4] Expenditure (or consumption) data reflect the effects of these informal transfers, whereas income data do not. The final factor in favour of expenditure data is that they are considered to be recorded more accurately than income (Grootaert, 1983). Therefore, the variable used to indicate living standards in this study is total expenditure, where this includes imputations for self-produced items, stock changes, and rent of owner-occupied dwellings.

To correctly indicate living standards, the household expenditure data require deflation to capture differences in needs and in prices faced by different households. Previous research in Papua New Guinea has assumed an adult equivalence scale where children aged less than 15 years count as 0.5 adult-equivalents and everyone else counts as 1.0 (Morauta, 1984). Deaton and Muellbauer (1986) show how an Engel method, using the budget share for food, overestimates child costs, while a Rothbarth method, using expenditures on adult goods, underestimates child costs. Applying these two methods to these data, and also comparing recommended calorie intakes, suggested that the cost of a child in the 0-6 age group was between 48 and 68 percent of the cost of an adult but the cost of an older child was equal to the cost of an adult. Therefore, the equivalence scale used here is that all children age six and below count as 0.5 adult-equivalents, and everyone else counts as 1.0.

In addition to differences in household composition, differences in the number of people also cause needs to vary between households. Studies of poverty in developing countries usually assume that the cost of living rises one-for-one with the number of people in the household but Lanjouw and Ravallion (1995), after applying a variety of methods, concluded that there are substantial economies of size facing poor households. However, when these methods are applied to the current data, results are less definite (Gibson, 1996). An Engel method suggests that the elasticity of the cost of living with respect to household size is approximately 0.7 but a Rothbarth method suggests that the cost of living rises one-for-one with household size. Therefore, the results presented in this paper follow convention by using expenditure per adult-equivalent as the welfare indicator, with no allowance for size economies.

The incorporation of price differences can be achieved by deflating expenditure per adult-equivalent by a cost of living index. The consumer price index was used for this purpose, deflating prices spatially between urban areas and temporally between quarters and years. The consumer price index was not available for one urban area in the sample so the records of individual purchases from the expenditure diaries of households in that area were used to construct a price index. The constructed price index was based on goods of exactly the same specification as used in the consumer price index regimen, and by being derived from individual

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[4] As evidence of this point, the Gini coefficient for household income is 0.49 while for household expenditures it is only 0.40.

transactions it avoided quality and measurement error biases due to the use of “unit values” (Deaton, 1988).

The Poverty Line

The poverty line is set in three steps. First, a basket of locally consumed foods that provides daily food energy requirements is formed. Then the cost of purchasing this basket of foods in each urban area is estimated. This cost is referred to as the “food poverty line”. Finally, an additional allowance is added for the consumption of non-food items. In many developing countries two alternative specifications of the non-food allowance are used, one which provides a lower, more austere standard of living, and one which is more generous (Ravallion, 1994). The same approach is used in this study.

The basket of foods is formed from the actual consumption patterns of the poorest one-quarter of households in the sample (ranked by real expenditure per adult-equivalent). This basket provided an average of 1600 calories per adult-equivalent per day, whereas requirements are 2200 calories per day. The difference is covered by scaling the food basket by a factor of 1.4 (=2200/1600). Details of these calculations, and the weights for the foods in the basket, are reported in Gibson (1996).

The austere allowance for non-food items is based on the typical value of non-food spending by households whose total expenditure just equals the cost of the food poverty line. Consuming these non-food items means that some food needs are ignored, so the non-food items can be considered as essentials (Ravallion, 1994). The average food share for these households (in urban area *j*) is found from the following Engel curve:

$$w = a + b \ln\left(\frac{x}{n \cdot z_j^F}\right) + \sum_{k=1}^{K} g_k n_k + \sum_{j=1}^{J-1} f_j D_j + e \qquad (1)$$

where w is the food budget share, x is total expenditure, n is the number of persons, z_j^F is the food poverty line for an adult-equivalent in area j, n_k is the number of people in the kth demographic category, and D_j is an intercept dummy for the jth urban area. When total expenditure exactly equals the cost of the food poverty line, $\ln\left(x/\left(n \cdot z_j^F\right)\right) = 0$, so $a_j = \hat{a} + \sum_{k=1}^{K} \hat{g}_k \bar{n}_k + \hat{f}_j$ gives the average food share in urban area j, where $\bar{n}_k$ is the mean of the demographic variables for the households used to form the poverty line basket of foods. The lower poverty line for the jth area, z_j^L is given by the sum of the food and non-food components, $z_j^L = z_j^F + z_j^F(1-\alpha_j) = z_j^F(2-\alpha_j)$.

A more generous allowance for non-food items can be found from the typical value of non-food spending by a household whose food spending actually reaches the food poverty line. Finding the food share, *w** at this expenditure level requires a numerical solution, characterised by $n \cdot z_j^F = x \cdot w^*$. This can be substituted into equation (1) to give:

$$w^* = a_j + b \ln\left(w^*\right)^{-1} \quad .$$

Using w-1 to approximate $\ln w$, an initial solution of $w_0=(\alpha_j+\beta)/(1+\beta)$ can be found. This estimate can be improved upon by iteratively solving the following equation, *t* times:

$$w_t^* = w_{t-1}^* - \frac{(w_{t-1}^* + b \ln w_{t-1}^* - a_j)}{1 + b \big/ w_{t-1}^*}$$

and the upper poverty line is estimated as $z_j^U = z_j^F \big/ w^*$ (Ravallion, 1994). Two iterations were sufficient to obtain stable estimates of *w**.

The Poverty Index

The most common measure of poverty is the *Head-count Index*, which gives the proportion of the population with a standard of living below the poverty line. However, the head-count index doesn't indicate how poor the poor are, and hence doesn't change if people below the poverty line become poorer. The *Poverty Gap Index*, which is the average over all people, of the gaps between poor people’s standard of living and the poverty line, expressed as a ratio to the poverty line, does show the average depth of poverty. However the poverty gap index is not sensitive to the distribution of living standards among the poor. For example, in a population with four poor people, the poverty gap index is the same whether all four consume at 80 percent of the poverty line, or one has a consumption level that is only one-half of the poverty line while the other three are at 90 percent of the poverty line. To make the poverty gap index sensitive to the distribution of living standards among the poor, the poverty gaps of the poorest people can be given a bigger weight when calculating the index.

The head-count index, the poverty gap index, and the distributionally sensitive measure can all be estimated using the same general equation, through choice of values for a poverty aversion parameter (Foster, Greer and Thorbecke, 1984). The equation is:

$$P_a = \frac{1}{n} \sum_{i=1}^{q} \left(\frac{g_i}{z} \right)^a \qquad (2)$$

where the poverty line is z, the value of expenditure per capita for the ith person's household is y_i and the poverty gap for individual i is $g_i = z - y_i$. Total population size is n and q is the number of poor people (those where $y_i < z$). When parameter α is set to zero, P_0 is simply the head-count index. When α is set equal to one, P_1 is the poverty gap index, and when α is set equal to two, P_2 is the modified poverty gap index that is distributionally sensitive to the severity of poverty.

There are some interesting interpretations of the P_a measures. When P_1 is multiplied by the poverty line z, and by the population size n, it gives an estimate of the size of resources needed to eradicate poverty if it was possible to perfectly target resources to the poor. This can be verified from equation (2), where all that is left after multiplying by z and n is the sum of all poverty gaps. If targeting was completely impossible, and government knew nothing about who was poor and who was not, then the only transfer that could guarantee the elimination of poverty would be to give everyone in the population a transfer payment equal to the poverty line, so the total cost would be $z.n$. Therefore, the ratio of the minimum cost of eliminating poverty with perfect targeting to the maximum cost with no targeting is simply P_1, which can be interpreted as an indicator of the potential saving to a poverty alleviation budget from targeting (Ravallion, 1994).

The Probit Equation

Multivariate analysis is used to determine which characteristics of households are associated with being poor. Although ideal data would describe the characteristics and poverty status of each individual person such data are not available so the poverty status of households and the characteristics of the household head are used as substitutes. The three poverty lines and the three poverty indexes that have been described combine to give nine possible dependent variables for the multivariate analysis. Only two of these dependent variables are used: the head-count index evaluated at both the lower and upper poverty lines. The head-count index is used because of the widespread concern of policy makers with the *incidence* of poverty: how many are poor and what are their characteristics? The lower and upper poverty lines are used because they set bounds on the value of any reasonable poverty line (Ravallion, 1994).

The head-count index is based on a 0-1 variable; $h_i = 1$ if the ith household's expenditure per adult-equivalent, y_i is less than the poverty line, z. Therefore, probit estimation is appropriate,

$$\Pr\langle h_i = 1 | \mathbf{X}_i \rangle = \Phi(\mathbf{X}_i \mathbf{b}) \tag{3}$$

where Φ is the standard cumulative normal. The matrix of explanatory variables, $\mathbf{X}$ includes household size, along with the educational attainment, employment status, age, gender, and migrant status of the household head, and dummy variables for each urban area. The coefficient vector $\mathbf{b}$ in equation (3) measures the impact of a change in the explanatory variables on the standard cumulative normal but policy makers are more likely to be concerned with the impact of the explanatory variables on the probability of a household being poor. Usually with probit models a 'probability derivative' can be calculated for an infinitesimal change in, say, variable x_1 evaluated at the mean of the other variables, using the formula:

$$\frac{\partial \mathrm{P}}{\partial x_1} = f(\bar{\mathbf{x}}\mathbf{b})b_1 \tag{4}$$

where f is the normal density.

Equation (4) is not appropriate in the current study because three of the explanatory variables are discrete (household size, age and years of schooling of the head), while the others are dummy variables. Instead, the probability derivative for each discrete variable is calculated using a one-unit change in that variable, holding the other discrete variables at their mean. This probability derivative is evaluated at all 144 possible combinations of the (dichotomous) characteristics of the household head (where 144 is the product of six employment states, two gender states, two migrant states, and six regional dummies). Putting the discrete variables in the first three columns of **X** and letting a^* represent the combined value of the intercept plus the dummy variables that are 'switched on' by the household head's characteristics, the probability derivative for the first discrete variable is given by:

$$\frac{\partial \mathrm{P}}{\partial x_1} = \Phi\left(b_1(\bar{x}_1 + 1) + b_2\bar{x}_2 + b_3\bar{x}_3 + a^*\right) - \Phi\left(b_1\bar{x}_1 + b_2\bar{x}_2 + b_3\bar{x}_3 + a^*\right). \tag{5}$$

Reporting all 144 estimates of $\partial \mathrm{P}/\partial x_1$ for the various combinations of the dummy variables is not feasible, so instead a weighted average of these estimates is reported where the weights are the frequency with which each combination of characteristics occurs in the data.

The probability derivative for a dichotomous characteristic is calculated as the change in probability as the dummy variable is switched from "0" to "1", holding the discrete variables constant at their means. This change in probability depends on which of the other dummy variables are 'switched on', so the derivative is calculated at all feasible combinations of the other dummy variables and the weighted average of these estimates is reported.[5] These weighted averages of the probability derivatives give some sense of which explanatory variables have the biggest impact on the risk of being poor but they may disguise important interaction effects that could be important for targeting. For example, the effect of an additional year of schooling for the household head might be different for a smaller household than for a larger household.[6] Therefore, some of the main interactions effects are also reported.

[5] There are 72 feasible combinations of the other dummy variables when the probability derivatives for either the gender or migrant status dummy variables are calculated, and 24 when the derivatives for any of the employment status variables are calculated.

[6] I am grateful to an anonymous referee for suggesting this.

4. Results[7]

The need for intervention to protect the poor during structural adjustment will depend in the first instance on how badly off the poor were before the adjustment programme began. The analysis begins, therefore, with estimates of overall poverty rates. One of the most identifiable characteristics of the poor is where they live, so the poverty estimates are disaggregated by province of residence.[8]

Over one-third of the urban population surveyed is classified as poor, using the upper poverty line (Table 1). This poverty line has a generous allowance for non-food expenditures so the more austere living standard allowed by the lower poverty line may be more widely used as a standard by policy makers. At this lower poverty line, approximately 20 percent of the urban population are poor. Common to both poverty lines is a small group, of 6.4 percent, who are food-poor in the sense that they cannot meet their daily calorie requirements, even if they were to spend all of their income on the basic food basket. Combining the head-count index and the poverty gap estimate shows that the average expenditure level of poor people was just over three-quarters of the value of the lower poverty line ($1\text{-P1}/P_0$=0.78).

The National Capital District (which is made up mainly by Port Moresby) had the highest incidence of poverty at the lower poverty line and had the second highest head-count index at the upper poverty line. The National Capital District also had the highest values for the poverty gap and poverty severity indexes at the upper poverty line. The second largest city – Lae – also had a high level of poverty, with the largest value for the P_0 index and the second largest values for the P_1 and P_2 indexes at the upper poverty line. The highlands town of Goroka had the largest proportion who were very poor and could not afford the food poverty line. This high incidence of severe poverty in Goroka is also shown by the P_2 poverty severity index. The lowest incidence of poverty, according to all poverty lines and poverty measures, was in North Solomons province, where the Bougainville copper mine was located.[9]

Completely eliminating urban poverty by making perfectly targeted transfers that raise the expenditure level of the poor to the lower poverty line would cost

[7] All results are estimated using STATA™ 5.0 (StataCorp, 1997).

[8] In some provinces the UHS sampled households just in the main town and adjacent peri-urban villages, while in other provinces it sampled households from several towns. If the sample comes mainly from one town in a province, the name of the town is used rather than the name of the province when describing the results.

[9] Living conditions in this province are now much worse due to the closure of the mine and ongoing civil war.

Table 1. Estimates of Poverty Rates Disaggregated by Region

	Headcount (P_0) %	Poverty gap (P_1) %	Poverty severity (P_2) %
Upper Poverty Line	**37.5**	**11.0**	**4.5**
National Capital District	46.1	14.2	6.0
Goroka	41.7	12.0	5.0
East Sepik	36.0	10.3	4.1
North Solomons	8.9	1.8	0.5
Rabaul	32.1	8.9	3.3
Lae	50.8	13.8	5.6
Lower Poverty Line	**19.6**	**4.4**	**1.6**
National Capital District	23.9	5.2	1.9
Goroka	20.2	5.6	2.1
East Sepik	21.2	4.5	1.7
North Solomons	3.8	0.7	0.1
Rabaul	21.1	4.4	1.4
Lae	18.3	4.4	1.8
Food Poverty Line	**6.4**	**1.3**	**0.4**
National Capital District	7.1	1.5	0.5
Goroka	10.2	2.1	0.6
East Sepik	6.0	1.5	0.6
North Solomons	0.7	0.0	0.0
Rabaul	6.0	0.9	0.3
Lae	8.1	1.7	0.4

approximately K20m per year in 1997 terms.[10] This estimate is derived as follows: (i) the weighted average value of the lower poverty line is approximately K900 per adult equivalent per year, (ii) the 1990 Census estimate of the urban population, in adult-equivalent terms, is approximately 500,000, (iii) multiplying z=900 by n=500,000 by P_1=0.044. With no targeting, and just making a poverty line-sized transfer to all urban residents, the cost of complete poverty elimination would by K450m per year.[11] Hence, there are potentially large savings from targeting interventions just to the poor.

Which characteristics of the poor should be used to make such well-targeted interventions? The results in Table 2 may help to answer this question. Three

[10] It would take K70m to raise the expenditure level of the poor to the upper poverty line.

[11] Incentive effects and induced migration into urban areas are assumed absent in this analysis, which is designed mainly to show the potential economies from targeting.

characteristics appear to have a statistically significant effect on the probability that a household is poor, and this effect is apparent at both poverty lines. These three characteristics are the size of the household, and the years of schooling and employment status of the household head. The characteristics whose effects are not statistically significant are the age, gender and migrant status of the household head.

Larger households appear to be poorer; on average, adding a person to a household of mean size (n=5.8) raises the risk of that household falling below the lower poverty line by two percentage points.[12] The effect is larger at the upper poverty line, with a 4.1 percentage point increase in the risk of poverty. These effects of household size on poverty are calculated as averages over all possible combinations of dummy variables, for households whose head is of average age and years of schooling. The effect on poverty of some of these other variables interacts with the effect of household size, and this will be illustrated below.

The risk of poverty is lower, the higher the level of schooling of the household head; on average, an extra year of schooling beyond the mean (6.4 years) reduces the risk of falling below the lower poverty line by 1.4 percentage points. This extra year of schooling reduces the probability of the household falling below the upper poverty line by three percentage points. It appears that basic schooling is the most useful type of education for reducing poverty because dummy variables for academic and vocational post-school qualifications had no effect on the risk of poverty.

Changes in the employment status of the household head have the largest effect on poverty of any of the variables listed in Table 2. On average, there is a 17 percentage point increase in the risk of poverty for a household whose head loses a job in the public sector (the excluded employment state in the model) and becomes unemployed. The increased risk of poverty is even greater, at 24.4 percentage points, when the upper poverty line is used. There is also a large rise in the risk of poverty (15 percentage points) if the household head becomes a non-participant in the labour market, and the size of this effect does not depend on which poverty line is used. The probability derivatives also suggest that there is a premium for working in the public sector separate from the effect of having a job: moving a household head from a public sector job to a private sector job raises the risk of poverty by seven percentage points.

Some changes in employment status do not alter the likelihood that a household is poor. If a household head moves from a public sector job to operating a formal business there is a small but statistically insignificant drop in the risk of poverty.

[12] The implication of this result depends on size economies being absent. If there are size economies, lower expenditure per person in larger households does not necessarily indicate that the people are worse off than the residents of smaller households with higher per capita expenditures.

Table 2. Probability of Being in Poverty Based on Characteristics of Household Head

Explanatory Variables	Mean	Lower Poverty Line: Probit coefficients	Lower Poverty Line: $\partial P/\partial X$ %	Upper Poverty Line: Probit coefficients	Upper Poverty Line: $\partial P/\partial X$ %
Household size	5.78	0.112**	2.0	.138**	4.1
		(0.015)		(0.014)	
Years of schooling	6.43	-0.085**	-1.4	-0.109**	-3.0
		(0.016)		(0.014)	
Age of head	37.4	-0.003	-0.0	-0.006	-0.2
		(0.005)		(0.005)	
Employed in private sector	0.39	0.372**	6.0	0.237**	6.7
		(0.135)		(0.114)	
Works in own (formal) business	0.05	-0.189	-2.1	-0.118	-2.9
		(0.286)		(0.227)	
Works in informal sector	0.05	-0.042	-0.5	0.019	0.5
		(0.254)		(0.211)	
Unemployed and job searching	0.02	0.819**	17.1	0.754**	24.4
		(0.288)		(0.271)	
Not in the labour force	0.10	0.740**	14.8	0.490**	15.0
		(0.169)		(0.159)	
Female household head	0.04	0.005	0.1	0.290	9.0
		(0.296)		(0.230)	
Migrant head	0.81	-0.109	-1.9	-0.161	-4.8
		(0.136)		(0.119)	
Constant		-1.421		-0.755	
Pseudo-R^2		0.20		0.24	
Log likelihood		-350.81		-495.09	
Restricted (slopes=0) Log-likelihood		-440.77		-648.06	
Joint significance test χ^2 (15 df)		179.93**		305.95**	
Percent correct predictions		85.8		76.2	

Note: Standard errors in ( ), **=statistically significant at the 5% level;, *=statistically significant at the 10% level.

Dependent variable is a binary variable taking a value of 1 if the household's expenditure per adult-equivalent is below the poverty line and 0 if it is not. When poverty is measured at the lower poverty line, 152 observations=1 and 941 observations=0. When poverty is measured at the upper poverty line, 306 observations=1 and 787 observations=0.

The excluded economic activity group is households where the head has a public sector wage job (38 percent of total).

Intercept dummy variables for each town are included to control for differences in regional poverty rates. $\partial P/\partial X$ is the change in the risk of being poor given a unit change in the independent variable (evaluated at the mean for continuous variables and as a switch from "0" to "1" for dummy variables).

Moving to the informal sector brings no change in the risk of poverty, which seems surprising because many informal sector workers, such as street vendors, appear to be poor.[13] But one reason why informal sector workers are poor is their low education: they average only 2.2 years of school compared with 7.8 years for public sector employees. So the thought-experiment represented by $\partial P/\partial X$ in Table 2, which switches someone from a public sector job to the informal sector while holding their educational level constant, is not the same as an unconditional comparison of the informal and public sectors. The higher rate of poverty in the informal sector seems to be due to the low level of education of workers in that sector rather than to intrinsic features of the sector itself.

The age of the household head appears to be unrelated to the risk that the household is poor, and this result also holds if a quadratic in age is added to the model. Female-headed households have some unfavourable characteristics which are associated with a higher risk of poverty: (i) a lower level of schooling (5.7 versus 6.4 years), and (ii) a lower rate of wage employment (67 percent versus 77 percent), but after controlling for these factors, female-headship *per se* is not a cause of poverty. It is interesting, however, that female headship is the characteristic with the biggest change in $\partial P/\partial X$ when the definition of poverty shifts from the lower to the upper poverty line. This may indicate that female-headed households are bunched below the mean of the expenditure distribution but above the lower poverty line.

Interaction Effects

There are many interaction effects that could be reported but there is a potential cost of such detail. The screening costs of characteristic targeting rise with increases in the number of characteristics, and interactions of characteristics, that are used to target interventions. Therefore, the interaction effects reported are restricted to those involving the three statistically significant characteristics: the size of the household, and the years of schooling and employment status of the household head.

The marginal benefit of schooling, in reducing the risk of poverty, is greatest when the household head has a low initial level of schooling (Figure 1). An extra year of schooling for a household head who has completed only one year of schooling would reduce the risk of poverty by 2.2 percentage points, while that extra year when 10 years are completed reduces the risk by only 0.9 percentage points.[14] Additional years of schooling for the household head are also more beneficial, the larger is the household. For example, an extra year of schooling for the head of a 10-member household reduces the risk of poverty by 2.5 percentage

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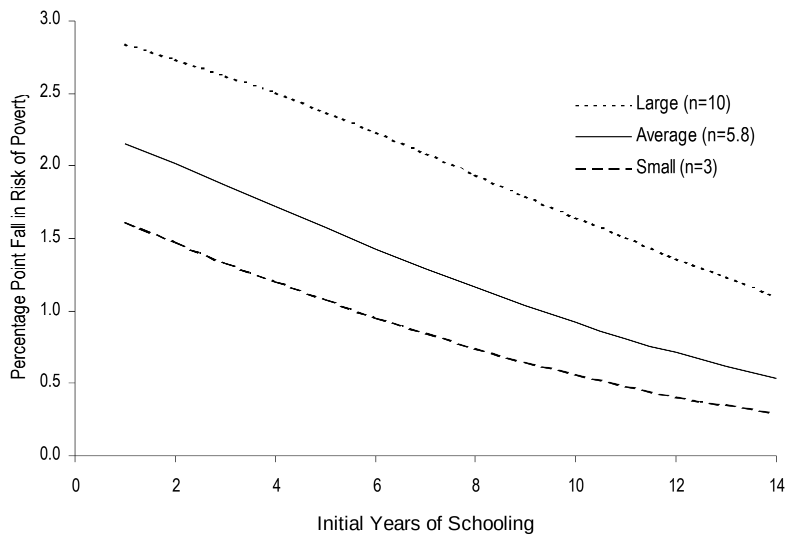
[13] This is borne out by the poverty rate for households headed by an informal sector worker (15 percent) compared with the rate for households with a public sector worker (8.8 percent). However, both poverty rates are much less than those for households whose head is a non-participant (34.8 percent) or a job-seeker (32.0 percent).

[14] This finding is consistent with other evidence on rates of return to different levels of schooling in developing countries (Psacharopoulos, 1994).

points if that head already has four years of schooling. But if that same person was the head of a three-person household the extra year of schooling would reduce the risk of poverty by only 1.2 percentage points.

Figure 1. Effect of an Extra Year of Schooling for the Household Head in Reducing the Risk of Poverty



The increased risk of poverty for a household whose head loses a job in the public sector and becomes unemployed is worse if the household is large (Table 3). For large households (ten members) the average value of ¶P/¶X when the head is moved from the public sector into unemployment is 24.7 percentage points, but for small households (three members) it is only 12.0 percentage points. The effect of unemployment is also amplified if the household head has a low level of schooling: with only three years of school the average value of ¶P/¶X is 21.9 percentage points, but with nine years of school ¶P/¶X falls to 13.4 percentage points. There are also small increase in the effect of unemployment if the household has a head who is either a non-migrant or a woman.

5. Conclusions and Policy Suggestions

The results suggest that urban poverty was a serious problem in Papua New Guinea prior to the structural adjustment program. The small budget for poverty alleviation means that interventions need to be well-targeted if the urban poor are to be protected during the structural adjustment. The probit results suggest that interventions should be targeted towards larger households, where the head is unemployed and has lower levels of schooling. This raises the question of what type of programs can be restricted to just households with these characteristics.

Table 3. The Effect of Unemployment on the Risk of Poverty as Other Characteristics Vary

Household Size		Years of Schooling of Head	
Small (*n*=3)	Large (*n*=10)	Low (*n*=3)	High (*n*=9)
12.0	24.7	21.9	13.4
Gender of Household Head		**Migrant Status of Household Head**	
Male	Female	Migrant	Indigenous
17.0	18.9	16.5	19.5

Note: Values are the percentage point increase in the risk of poverty as a household head is switched from a public sector job to unemployment. The average value of this increased risk, over 24 combinations of region, gender and migrant status of the household head, and when household size, age and years of schooling of the head are at their average values, is 17.1 percentage points.

Experience from other countries suggests that labour intensive public works programs can be targeted towards the poor by setting a daily wage that is low enough to deter people who are not poor. An example of such public works employment programs is the Employment Guarantee Scheme of Maharashtra State in India, which has been shown to target transfer benefits to poor households who are characterised by having low pecuniary opportunity costs of participating (Datt and Ravallion, 1994). There may be scope for this sort of scheme in Papua New Guinea because lack of maintenance of public infrastructure, especially roads, has been a major problem since Independence. One concern with schemes that add to employment in urban areas is that they might increase urban migration, but this need not occur if the structural adjustment program successfully improves the level of public services in rural areas. In particular, if roads are improved rural households will have access to a wider range of food and cash crop markets, reducing the incentive to migrate.

Education programs to let adults complete more grades of community (primary) school would also target the poor. People who have already completed these grades (and who have a lower risk of being poor, according to the results in Table 2) would have no reason to repeat those classes. Therefore, this 'second-chance' schooling would tend to target the poor. The case for programmes that let adults complete higher levels of schooling is weaker because of the declining marginal effect of schooling on the risk of poverty (Figure 1).

Programs that reduce the cost to large households of user charges for public services (especially school fees) would also target the poor. Some areas of Papua New Guinea already operate such a system for community school fees: if a family has three of more children in the same school, they do not have to pay fees for the third (or any subsequent) child. This system could be extended to adult education, and possibly to health services.

In addition to these practical conclusions, this study illustrates that relatively simple techniques such as applying a limited dependent variables model to a poverty index can be useful for providing policy advice for protecting the poor during structural adjustment. The study also illustrates the value of household survey data for assessing the existing level of poverty and designing policies that might alleviate the worst effects of structural adjustment on the poor.

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