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Measuring the impacts of agricultural research on poverty reduction

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Abstract

Policymakers are increasingly calling upon agricultural research managers to consider poverty reduction objectives when making resource allocations. The authors present a simple method to measure the impact of agricultural research on the poor. This method has the advantage that it presents the results in a manner consistent with commonly used measures of poverty. This consistency and focus should facilitate and enhance dialogue between policymakers and research managers when deciding on resource allocations and assessing impacts on poverty reduction. An illustrative application is presented using data from Malawi.
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1. Introduction

Increased agricultural productivity has been the primary engine of economic development in most less developed countries (LDC). Technical change in agriculture, the major source of increased productivity, requires sustained investments in agricultural research and extension. Substantial returns to agricultural research have been reported in different countries throughout the world. In recent years, however, agricultural research programs have come under increased scrutiny for several reasons (Alston et al., 1998; Byerlee and Alex, 1998). First, during the 1990s many LDCs carried out policy reforms that reversed traditional biases against agriculture and led to changes in the relative profitability of different commodities. Such returns raise the question of whether research priorities are appropriate under new policy regimes. Second, and sometimes related to these broad policy reforms, budgets for publicly funded agricultural research have been declining. Third, there has been increasing pressure to direct publicly funded agricultural research towards the needs of small-scale farmers and the rural poor. As a result, policymakers are increasingly calling upon research managers to explicitly consider poverty reduction objectives when carrying out priority-setting exercises and making resource allocations (Byerlee, 2000).

Although increased agricultural productivity can benefit the poor in a number of ways, ongoing debates exist about how the benefits of technical change are distributed among sub-groups within countries. Some

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are concerned that most of the benefits of agricultural research generally accrue to better-endowed farmers and to urban consumers, often bypassing poor rural producers. Others claim that, except under unusual circumstances, the rural poor are generally able to share in the benefits of technical change, especially when productivity gains induce lower food prices (Binswanger and von Braun, 1993). A recent review of the impacts of agricultural research on the poor (Kerr and Kolavalli, 1999) shows that it is difficult to make generalisations about the impacts of agricultural research on the poor and the distribution of benefits depends on underlying social and political institutions rather than the specific technology, per se.

Agricultural research in Sub-Saharan Africa (SSA) has followed a unique evolutionary path and African policymakers are now focusing on using research to reduce poverty.[1] At independence, most SSA countries inherited research systems that were staffed by European scientists and whose priorities reflected interests of the former colonialists. High priority was given to export-oriented crops produced on large-scale commercial farms. Following independence, re-orientation of the systems occurred only gradually, because governments sought to stimulate export earnings and employment growth based on large-scale commercial agriculture. Publicly funded SSA research also relied heavily on donor support and donors, especially through the 1970s and 1980s, were interested in using large-scale commercial farming as an engine of growth. Beginning in the mid-1980s, however, both donors and SSA governments began to question the commercial orientation of agricultural research. This re-examination was due to the limited effectiveness of export-oriented growth, growing concern for poverty and inequality, and increasingly tight budgets. The needs of small-scale farmers became more prominent in policy discussions and the desire to use agricultural research to reduce pressing rural poverty became imperative.

Studies of agricultural research in SSA countries have shown mixed, but generally positive rates of return (Masters et al., 1998; Oemke et al., 1997; Rukuni et al., 1998). Rukuni and Blackie cite three studies with negative rates of return and another with a surprisingly small one, but most estimates of returns range in the 30–60%. Oemke et al. (1997) show evidence that while agricultural productivity growth may be necessary to achieve overall economic growth in SSA, it is not likely to be sufficient. They also find that SSA agricultural research systems have had a number of successes since independence, but institutional failures among national agricultural research systems have hindered political support for agricultural research. Friswold and Ingram (p. 59) report: "... research has yet to generate broad sectoral productivity growth in SSA agriculture". Agricultural research in SSA is now coming under heavy scrutiny because aggregate growth rates in the region have not been impressive and because of growing concern for poverty reduction. With an increased focus on poverty outcomes, SSA research managers need improved means of evaluating impacts on poverty of alternative agricultural research portfolios.

The purpose of this paper is to present a simple method to measure the impact of agricultural research on poverty and inequality. The method can be used in an ex ante research priority-setting exercise to help allocate resources for agricultural research. It represents a departure from rate of return studies by shifting the focus to ex ante allocations of research resources and by explicitly incorporating a poverty focus. In contrast to widely used economic surplus methods for estimating, ex ante, the benefits of alternative agricultural research portfolios, the proposed method has the advantage that it is consistent with commonly used measures of poverty and inequality. This consistency and focus should help facilitate and enhance dialogue between policymakers and agricultural research managers. The method can be implemented with relative ease using household survey data that are readily available in many LDCs. An illustrative application of the method uses data from Malawi.

2. Background on measuring research impacts and measuring poverty

2.1. Agricultural research evaluation: economic surplus analysis

The most widely used means of ex ante evaluation of the impacts of agricultural research is through eco-

[1] See Rukuni et al. (1998) for an excellent overview of the evolution of SSA agricultural research systems.

nomic surplus analysis in a partial equilibrium framework (Alston et al., 1995). When surplus analysis is used to examine the impacts of agricultural research on the poor (producers and consumers), households are usually grouped according to expenditure quintiles, or by some other means of distinguishing between poor and non-poor households. Parameters (such as the likelihood of technology adoption, supply and demand elasticities) are estimated for the respective sub-groups (e.g. smallholders versus larger-scale commercial farmers, by agro-ecological zone, household headship), and the surplus gains and losses associated with each research portfolio are evaluated.

Mills (1997) and Mutangadura and Norton (1999) are recent examples of analyses based on economic surplus methods that focus on the distributional impacts of agricultural research. Mills (1997) evaluates the expected impacts of sorghum research on producers and consumers in Kenya using a spatial multi-market model, for four agro-ecological regions. Mutangadura and Norton (1999) use farm types (large- and small-scale farmers), and agro-ecological region (high/low potential) to distinguish between agricultural research impacts on different producer groups in Zimbabwe. Researchers were asked to estimate the productivity gains and probability of adoption of their research results under different assumptions about funding. Economic surplus gains and adoption rates for producers were estimated separately for farm types and regions and were used to generate net present values. These values are incorporated into a multi-objective linear programming mode, which is run with different weights placed on objectives (efficiency and equity). Although surplus gains and losses can be disaggregated by sub-group, there is no direct measure of the impact on absolute or relative poverty of the groups, and differences among households within broad sub-groups are ignored.

Surplus measures can also be used in an ex post evaluation framework. Ex post, surplus changes can be measured using elicitation methods, or econometrically. In the former, scientists are asked to estimate the supply shift resulting from a historical research program (e.g. Norton and Alwang, 1997). Alternatively, supply shifts can be measured econometrically, using appropriately lagged research expenditure variables, and surplus can be computed from these estimates. In both cases, rates of return to research are straightforward to compute using research expenditure or cost data.

One disadvantage of surplus methods, as they are commonly used, is that they do not provide clear-cut evidence about the impact of a research program on measures of aggregate poverty. Thus, a divergence emerges between research priority-setting (and evaluation) efforts and national dialogues about poverty reduction. In such dialogues, commonly understood measures of poverty are used, and policymakers and research managers need information on how increased research resources or a different allocation of resources among crops will affect these measures. Such information should facilitate and improve communication on research objectives and tradeoffs subject to budgetary constraints.

2.2. Poverty profiles and poverty measures

Poverty profiles (e.g. World Bank, 1996) are used to focus policy discussions, design and target programs and as baselines for systems of monitoring changes in poverty over time. A typical poverty profile begins with a quantifiable poverty line, uses household data to measure incomes or consumption relative to this line, and aggregates over households to create a measure of poverty. This measure, often of the Foster, Greer, Thorbecke (FGT)[2] class, can be decomposed to show how poverty varies across sub-groups of society, such as region of residence, household headship or sector of employment (Foster et al., 1984). FGT indices are additively decomposable; this decomposability facilitates poverty analysis (Ravallion, 1992).[3]

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[2] The FGT (see Foster et al., 1984) class of poverty measures is defined as $P_\alpha = \sum_{i=1}^{N}(z - y_i/z)^\alpha$, where N is the number of poor households, y_i the income or expenditures of the ith poor household, z the poverty line and is measured in the same units as is y, and α is a parameter of inequality aversion. When $\alpha = 0$, P_α is simply the headcount index (the prevalence of poverty), and when $\alpha = 1$, P_α gives the poverty gap index. For different values of α, the index provides information on different dimensions of the poverty problem.

[3] Additive decomposability means that the aggregate poverty measure, θ, can be decomposed as $\theta = \sum_{k=1}^{K} f_k\theta_k$, where there are K population subgroups (indexed by k), for example regions of the country, f_k is the proportion of households in the kth subgroup $\left(\sum f_k = 1\right)$, and θ_k is the measure of poverty for the kth subgroup. See Ravallion (1992) for a detailed discussion of additive decomposability, which he calls additivity. Using additivity, the contribution to overall poverty coming from a population sub-group

Typically, a poverty profile contains estimates of the impact of overall growth (in income or expenditures) on poverty. These measures, called growth elasticities, are usually computed under the assumption that the distribution of well-being is unaffected by the growth. The primary reason why growth elasticities are computed assuming no change in the Lorenz curve is that the inclusion of distributional changes requires specific assumptions about how growth will affect distribution. The resulting elasticity depends on the distributional assumption (Kakwani, 1993). As an example, consider the headcount (H) index of poverty (the percentage of total population below the poverty line (z)). The headcount of poverty is related to mean consumption (μ) via the formula $\mu L'(H) = z$, where $L'(H)$ is the slope of the Lorenz curve evaluated at z. A simple growth elasticity can be obtained using this relationship. $L'(H)$ can be inverted to examine the sensitivity of the headcount to changes in μ, holding the Lorenz curve fixed. The other FGT indices can be obtained using analogous relationships (Datt and Ravallion, 1992). The advantage of these relationships is that secondary data (e.g. information used to create the Lorenz curve) can be used to fit a parameterised Lorenz curve and yield elasticities of poverty reduction to growth without reverting to the primary data.

The problem with such methods is that aggregate income growth is rarely distributionally neutral. As an example, agricultural growth occurs through sequential adoption of technologies by regions, crop, agro-ecological and climatic conditions, etc. When growth is sector-specific or affects the distribution of well-being, then these simple methods are inappropriate. There are two ways that non-neutral growth can be incorporated into measures of sector-specific poverty–growth elasticities: (a) by utilising primary data or (b) by developing a more detailed decomposition of the poverty–inequality–growth relationship (i.e. modelling shifts in the Lorenz curve). In the following application, we use primary household-level data as well as information on how household income will be affected by agricultural research. The impact of research-induced changes in income is incorporated into a poverty profile-type exercise to add up the total impacts on poverty measures.

can be decomposed rigorously. Similar, the impacts on poverty of income transfers or economic growth in general can be assessed.

3. Method for measuring agricultural research impacts on poverty

The impacts of increased agricultural productivity on income distribution and poverty reduction depend on a number of factors. Often these factors are not easily quantifiable. For instance, cropping patterns might change following introduction of a new variety; changes in these patterns are difficult to predict. If increased productivity stimulates the demand for labour and the poor tend to be suppliers of off-farm labour, then indirect labour market effects such as increased employment and higher wages may exceed the direct effects of productivity gains on farming incomes of the poor. Kerr and Kolavalli (1999) find that these wage and employment effects of improved agricultural productivity may have weakened in recent years. Non-agricultural wages are now likely to have a stronger effect on agricultural wages than in the past and economy-wide wages tend to be determined outside of agriculture. Finally, agricultural productivity growth can stimulate broader development of the rural economy, which also contributes to poverty alleviation. This general equilibrium effect is felt only in the longer term. The method proposed here does not incorporate these higher-order general equilibrium effects and focuses on the first-order impact of agricultural yield changes associated with technology adoption. The accuracy of such a first-order approximation depends on the magnitude of these effects; however, this magnitude is difficult or impossible to know ex ante. With household-level data, income growth associated with crop-specific yield changes can be aggregated to create measures of change in poverty and inequality. As mentioned in the concluding remarks of the paper, an extension of the model presented here could involve general equilibrium modelling to capture changes in cropping patterns and labour market effects.

We begin with a model of income determination for small-scale agricultural producers. Define income to be the sum of farm profits (π) and off-farm income. For the ith household, farm profits can be defined as

$$\pi_i = \boldsymbol{A}_i \boldsymbol{Y}_i \boldsymbol{P} - \boldsymbol{A}_i \boldsymbol{c}_i \tag{1}$$

where $\boldsymbol{A}$ is a $1 \times J$ vector of acreage allocated to each of J crops, $\boldsymbol{Y}$ a $J \times J$ diagonal matrix of yields, $\boldsymbol{P}$ a J vector of prices and $\boldsymbol{c}$ is a J vector of per-acre costs of production. Changes in farm profits can be decomposed as

$$\Delta\pi_i = \Delta \boldsymbol{A}_i(\boldsymbol{Y}_i \boldsymbol{P} - \boldsymbol{c}_i) + \boldsymbol{A}_i \Delta \boldsymbol{Y}_i \boldsymbol{P} + \boldsymbol{A}_i \boldsymbol{Y}_i \Delta \boldsymbol{P} - \boldsymbol{A}_i \Delta \boldsymbol{c}_i \quad (2)$$

Eq. (2) shows the four major effects that crop-specific research (and technical change) has on household income and poverty. The first is through changing the allocation of acreage to each crop. Research produces new technologies that change the relative profitability of crops and induce acreage reallocations. The second is the change in yields due to the new technology. The third component of the effect of research is the effect of changed supplies on prices received by farmers. Price changes depend on the tradability of the commodity which is reflected in the elasticity of demand. With more tradable commodities (such as maize and other grains), research-related supply shifts are not likely to affect producer prices. When demand for the commodities is less elastic, the price change is likely to be negative. The final effect in Eq. (2) is through the impact of research and the new technologies that result in lower unit costs of production.

In a typical surplus analysis, the final three effects are modelled. The second and fourth factors are used to produce the k-shift (Alston et al., 1995). Then, the demand and supply elasticities determine, together with this k-shift, the resulting change in prices. Clearly an important determinant of the impact of increased research is the existing acreage allocation to each crop: crops that are widely produced by the poor are also those where yield changes are most likely to reduce poverty.

Eq. (2) can be used to compute the ex post expected farm profits for each household. When added to off-farm incomes,[4] the resulting incomes can then be compared to a poverty line and aggregated to form expected changes in poverty measures (see footnote 2). The poverty measures can be decomposed (see footnote 3) by social grouping, geographic area, etc. or it is possible to compute the percentage change in the measure (poverty headcounts, depth and severity) with respect to a specific allocation of agricultural research resources. The contribution of research-induced technical change to changes in inequality can also be computed using standard Gini decomposition techniques (e.g. Stark et al., 1986).

As a first-order approximation of the changes in farm profits and to illustrate the method, we focus in this example on the yield-enhancing effects of agricultural research (the second component of Eq. (1) and its impacts on per-acre cost reductions. Acreage changes can usually only be examined in an ex post fashion, and our purpose here is to illustrate how forecasted poverty changes from research can be used to inform research allocations. For simplicity, when applying the model we also do not incorporate price changes. However, predicted price changes could be incorporated through use of standard elasticity estimates. For instance, partial equilibrium analysis of the main crops could be conducted, using estimated supply and demand elasticities and the predicted k-shift. The resulting price changes could be entered as the $\boldsymbol{A}_i \boldsymbol{Y}_i \Delta \boldsymbol{P}$ component of Eq. (2).

For the ith household, the yield effect depends on the probability of adoption of the new technology. Define $\mathbf{Pr}_i$ as the $J \times J$ diagonal matrix of adoption probabilities for the ith household. The expected effect of the research program on farm profits becomes:

$$E[\Delta\pi_i] = \boldsymbol{A}_i \Delta \boldsymbol{Y}_i Pr_i \boldsymbol{P} - \boldsymbol{A}_i \Delta \boldsymbol{c}_i \quad (3)$$

Household-level data on acreage distributions, yields and costs can be obtained from agricultural household surveys. The probability of adoption of new technologies is then estimated using these data. The expected yield increase ($\Delta \boldsymbol{Y}$) associated with a change in research budgets can be elicited from research scientists, using expert opinion, participatory methods, or in a number of ways (Alston et al., 1995). The expected change in farm profits can be added to base agricultural and non-agricultural income and the resulting sum can be used to recompute the poverty indices.

Each of the n potential research portfolios can be evaluated in such a way, and $n \times 3$ vectors of yield changes, adoption probabilities and cost changes can be constructed. Just as the 'base yields' will vary from farm to farm, adoption probabilities will depend on

[4] Off-farm incomes may change as a result of agricultural research. For example research on export crops can increase the demand for labour, raising income-earning opportunities off-the-farm (Binswanger and von Braun, 1993). However, as noted above, the impact of off-farm income, a second-order effect, is not included in this analysis.

household-specific considerations such as human and physical asset bases, access to credit, etc.

Several clarifications are necessary to make Eq. (3) operational. First, $\Delta \boldsymbol{Y}$ can be computed for all crops at once; in such a case, $\Delta \boldsymbol{Y}$ would reflect expected yield changes for an entire research portfolio. Alternatively, expected yield changes could be predicted crop by crop. Second, $\mathbf{Pr}_i$, the vector of adoption probabilities, needs to be estimated for each household. In order to compute the expected change in poverty, each household must be assigned an expected income level. It is not correct to multiply Δy_{ij} by adoption probabilities, since households either adopt or fail to adopt the technology; a threshold adoption probability must be adopted and if the household-specific predicted probability of adoption exceeds the threshold then the yield change associated with the new technology should be applied. If the household-specific adoption probability does not exceed the threshold, research is not expected to have an impact on income. Because the poverty measures rely on household-specific information, forecasted technology parameters (yields and costs) have to be household-specific.

Alternatively, household-specific yield changes could be modelled using an adoption/intensity of adoption framework (see Feder et al., 1985, for an overview of the adoption literature). For instance, Smale and Leathers (1995) examine the intensity of adoption of hybrid maize in Malawi using a Tobit model. Such a model would explain the intensity of adoption which is measured using acreage allocated to hybrids. In our case, however, we are predicting the probability of adoption of a new innovation which may or may not be a new seed variety; we multiply forecasted yield changes, adjusted for the probability of adoption, by the existing acreage allocated to the crop in question.[5] Thus, the determinants of intensity of adoption are not of particular interest.

The methods described above are applied to Malawi. Malawi is of particular interest because agricultural research there has been designed to explicitly support broad development objectives. For instance, prior to the 1990s, the government's main development strategy was to support large-scale commercialised agriculture on estates (Smale, 1995). Estate owners valued yield-increasing maize varieties and the agricultural research system responded by releasing high-yielding dent maize varieties. These dent maize varieties were not widely adopted by smallholders because of undesirable taste and poor storage properties. Since the early 1990s, however, government objectives have changed toward poverty reduction, and research managers are being asked to respond to these new priorities.

4. Background information on Malawi

Agriculture in Malawi is characterised by a high degree of dualism between the smallholder and estate sub-sectors. Smallholders constitute about 80% of the population of Malawi and about 90% of the country's poor (World Bank, 1996). Smallholders devote most of their land, which average around 0.6 ha, to staple foods. Maize accounts for about 70% of the area planted to crops (World Bank, 1996). Maize yields are low, partly due to inappropriate maize technologies. Low yields and small landholdings are linked, since smallholders seek off-farm employment to finance maize purchases and other consumption requirements and often neglect their own fields (Alwang and Siegel, 1999).

The Government of Malawi's (GoM) Ministry of Agricultural and Livestock Development (MoALD) runs the publicly funded research and extension systems that serve smallholders. The estate sub-sector has its own research and extension services, which are, in general, funded by members. The major estate-focused research entity is the Agricultural Research and Extension Trust (ARET), which is funded by a 1% levy on sales at tobacco auction floors. The main MOALD research institution is the Department of Agricultural Research and Technical Services (DARTS). Research funding levels have been below the 2% target share of total agricultural GDP, and about 0.5 of the budget is donor-funded (GoM, 1999; Pardey et al., 1997). Returns to agricultural research in Malawi have been low relative to other countries in Sub-Saharan Africa and the rest of the world (Masters et al., 1998).

The research system is organised with researchers divided into commodity groups. Research priorities within commodity groups have been influenced by international agricultural research centres, with development of high-yielding varieties a major objective.

[5] See World Bank (1996), for details on the NSSA.

Maize research has been a priority, reflecting the role of maize in the Malawian diet and the long-standing maize bias in agricultural policy (Smale, 1995). The major success story of the Malawian agricultural research system came during early 1990s was the introduction of locally bred flinty hybrid maize varieties (Rukuni et al., 1998; Smale, 1995).

Following the demise of the Banda dictatorship in 1994, the elected Government articulated a development strategy with smallholder-led growth and poverty reduction as its cornerstones (GoM, 1995). The major thrust of this strategy is achieving smallholder food security (GoM, 1994). Reforms instituted through a structural adjustment program, adopted by the GoM in 1996, were designed to contribute to the poverty reduction objective (Zeller et al., 1998). Legal restrictions on production and marketing of crops, and on input marketing were annulled. The agricultural research and extension systems, however, have not been significantly restructured to serve smallholders in the changed policy environment. While most recognise that agricultural research alone cannot solve poverty problems as severe as those in Malawi, policymakers increasingly question how research can complement other poverty-reducing policies.

5. An illustrative application of the method to Malawi

To provide a baseline, we begin by calculating poverty indices (headcount, depth and severity) for Malawian smallholders. The data are taken from the National Sample Survey of Agriculture (NSSA), which was carried out during the 1992/1993 season by the Malawian National Statistical Office (NSO) (see footnote 5). As can be observed in Table 1, poverty is pervasive among Malawian smallholders.[6] Some regional differences are found, with poverty most pronounced in the more densely populated Southern Region where landholdings are smallest and soil-water conditions are least favourable.

Table 1
Smallholder poverty by region in Malawi

	Poverty indices		
	Headcount	Depth	Severity
All Malawi	41.6	20.2	13.2
Northern region	40.7	19.4	12.7
Central region	33.8	15.8	10.1
Southern region	47.3	23.6	15.5

Note: from NSSA 1992/1993. Poverty line used is the World Bank's (1996) relative poverty line.

Table 2
Distribution of research scientists by crop, crop acreage and yields, Malawi

	Estimated % of total scientist research time[a]	Estimated % of total smallholder land planted (1992/1993)[b]
Cereals	24	72
Tubers	17	2
Legumes and oilseeds	20	8
Fruits and ornamentals	9	NA
Industrial crops	13	4
Vegetable and spices	17	9
Burley tobacco	[c]	5

[a] *Source*: Agricultural Sciences Committee, National Research Council of Malawi, 1999. Percentages include all researchers in Malawi, including ARET and private institutions.

[b] *Source*: NSSA, which does not have reliable estimates of fruit and ornamental plantings.

[c] Burley tobacco is included in the industrial crops research portfolio.

Cropping and land use patterns are likely to have changed significantly since the time of the survey (due to the reforms and other factors such as changing relative prices). For example burley tobacco acreage shown in Table 2 is likely to have been severely underreported as smallholders were prohibited from planting and marketing most types of tobacco at the time of the survey. It is unlikely that smallholders in 1992/1993 would have reported illegal growing activities to the NSO. In addition, smallholder burley tobacco production has increased significantly, especially since the 1995/1996 growing season (Zeller et al., 1998). Despite these limitations, the NSSA data provide a good means of examining how agricultural research might affect smallholder incomes and how, in turn, income changes affect poverty.

[6] If, however, we were interested in how an improvement to an existing technology (say an improvement in an existing HYV seed variety), we might instead model the intensity of prior adoption. In such a case, we would simply allocate the yield increase to already-existing land planted to the HYV variety under the assumption that all current users of the technology in questions will also adopt the innovation. A probability/intensity of adoption model would not be necessary.

Relative distributions of scientist research time in DARTS and smallholder crop acreages are presented in Table 2. While the majority of smallholder land in 1992/1993 was planted to cereals (with about 70% planted to maize), a much smaller percentage of total scientist time is devoted to these crops. In contrast, a relatively high proportion of scientists' time is devoted to tubers. Overall, scientists devote about 3/5 of their time to staple food crops (cereals, tubers, legumes and oilseeds) which account for about 4/5 of smallholder land use, and the remainder of scientist time is allocated to fruits and ornamentals, industrial crops, vegetables and spices.

As a part of a priority-setting exercise conducted in 1994 by DARTS, research managers were asked to estimate crop-specific yield increases associated with a 50% increase in their budget. A subjective estimate of these forecasted yield increases is presented in Table 3. A notable problem with these elicited values, and one that tends to be common with ex ante studies, is that only small differences exist in the forecasted yield changes across the spectrum of research programs. Such similarities obviously increase the influence of current (in the survey year) cropping patterns on research's poverty-reducing impact. Other potential problems with elicitation methods include complementarity between research programs (and the difficulty in separating impacts of a single program), benchmarking, and strategic bias inherent in subjective data. For instance, research managers, knowing that favourable productivity estimates may lead to increased funding for their program, may overstate the potential. All these topics, and methods designed to address them, are covered in (Alston et al., 1995). If the method proposed here is used to examine, ex ante, the poverty reduction potential of alternative research portfolios, efforts to reduce such errors are required.

Table 3
Estimated yield changes and technology adoption rates from 50% increase in commodity-specific research budget

Commodity	Yield change (% increase)
Maize	25
Roots/tubers	20
Groundnuts	25
Other grain legumes	30
Vegetables	15
Cotton	15
Rice	20
Sorghum/millet	25
Oilseeds	20

Source: based on GoM (1999) and Mutangadura and Norton (1999). George W. Norton, who was involved in the priority-setting exercise in Malawi, helped produce these estimates.

A final problem made evident in Table 3 is the absence of burley tobacco, whose spread to smallholders has been touted as an engine of rural poverty reduction in Malawi (Zeller et al., 1998). Because burley tobacco research has historically been conducted by ARET, it is not included in DARTS planning and budgets. Burley tobacco is almost exclusively produced for export markets, with the benefits of productivity increases accruing primarily to producers. A private funding and research mechanism for burley tobacco can be justified for this reason. However, there are likely to be significant poverty-reducing spill-overs from burley tobacco research. Thus, burley tobacco research might be a public good and GOM might consider funding it or coordinating its funding by including it in the research planning process.

An important advantage of the model is that it can be used to create a profile of the impacts of research allocations on specific sub-groups of the poor. For instance, research impacts are disaggregated by region of residence in Table 8 and by household headship in Table 9. To generate these results, Eq. (3) was computed using the forecasted yield changes from Table 3 as an estimate of ΔY. Adoption was set as a binary variable taking the value of 1 if the forecasted probability of adoption exceeded the 25th percentile value (see below). The headcount index of poverty following implementation of each research program was recomputed using the 'forecasted' income from Eq. (3).

5.1. Results

A Probit model was used to create household-specific forecasts of the probability of adoption of new technologies. The variables predicting adoption of new technologies included human capital, access to family labour, farm size, the existence of off-farm earnings in the household and a dummy variable for region of residence. The adoption model is similar in structure to other models of household and farm characteristics as determinants of technology adoption (e.g. Nkonya et al., 1997; Feder et al., 1985).

Table 4
Summary statistics on variables in adoption model

Model variables	Description	All Malawi	Northern region	Central region	Southern region
Dependent variable	Use purchased fertiliser or pesticide = 1; no = 0	0.432 (0.495)	0.432 (0.495)	0.564 (0.496)	0.287 (0.453)
Male-headed	Yes = 1; no = 0	0.692 (0.461)	0.742 (0.437)	0.731 (0.443)	0.633 (0.482)
Head's age	In years	44.285 (15.715)	45.392 (15.997)	43.685 (15.364)	44.562 (15.968)
Age squared		2204.125 (1536.851)	2310.192 (1576.801)	2139.145 (1496.982)	2238.709 (1562.795)
Head's education	Primary education = 1; else = 0	0.300 (0.458)	0.271 (0.445)	0.316 (0.465)	0.294 (0.456)
Head's education	Secondary or higher = 1; else = 0	0.286 (0.452)	0.523 (0.499)	0.266 (0.442)	0.230 (0.421)
Off-farm income	For all household: yes = 1; no = 0	0.674 (0.469)	0.658 (0.474)	0.661 (0.473)	0.693 (0.461)
Land per capita	In acres per capita	0.186 (0.201)	0.280 (0.221)	0.220 (0.224)	0.150 (0.157)
Household size	In adult equivalents	5.047 (2.512)	5.598 (2.833)	4.975 (2.356)	4.940 (2.540)
Spouse's education	Primary education = 1; else = 0	0.198 (0.398)	0.216 (0.412)	0.218 (0.413)	0.169 (0.375)
Spouse's education	Secondary or higher = 1; else = 0	0.145 (0.352)	0.353 (0.478)	0.125 (0.331)	0.097 (0.296)
N		10984	1525	4908	4551

The model is used to predict the likelihood of adoption of new technologies, and the dependent variable needed to reflect this probability. We chose current use of chemical fertilisers or pesticides as the single dependent variable. This variable is used to represent the probability of adoption.[7] Approximately 42% of the sample used either or both of these inputs. The summary statistics, presented in Table 4, reflect the high rates of poverty in the south; land holdings are small, adoption of new technologies is significantly lower than in other regions, education levels are lower and the incidence of male-headed households is lower. Throughout Malawi, smallholder households are likely to receive income from off-farm sources; the proportion of households doing so in the south is higher than the rest of the country, also reflecting the relatively higher poverty there.

The adoption model (results shown in Table 5) yielded an acceptable fit and reasonable parameter

[7] The poverty line used here is the World Bank's relative poverty line for Malawi. It roughly corresponds to a basic needs poverty line computed by costing a 200 kg annual maize requirement and inflating for non-food basic needs. It was estimated that in 1992/1993 (the year of the NSSA survey), 80% of the people in rural smallholder households had incomes below US$ 55 per year, well below the US$ 1 per day poverty line used for international comparisons.

Table 5
Probit model results: probability of adoption of new technologies[a]

Model variables	Parameter estimate (S.E.)	Marginal effect[a]
Intercept	−1.630 (0.111)	
Male-headed	0.242 (0.030)	0.09377
Head's age	0.010 (0.005)	0.00379
Age squared	−0.0001 (0.000)	−0.0000561
Head's education	0.103 (0.032)	0.04046
Head's education	0.167 (0.036)	0.06578
Off-farm income	−0.133 (0.028)	−0.05220
Land per capita	1.658 (0.073)	0.64886
Household size	0.099 (0.006)	0.03869
Spouse's education	0.161 (0.034)	0.06353
Spouse's education	0.296 (0.041)	0.11701
Central[b]	0.598 (0.028)	0.23202
Northern[b]	0.125 (0.041)	0.04931
N	10983	
Psuedo R^2	0.123	
Log-likelihood	−6583.53	
	Actual	
	Adopt	Do not adopt
Predicted	2600	1326
	2149	4929

[a] Marginal effects represent the change in the probability given a marginal change in the independent variable. For discrete variables, the marginal effect is calculated over the discrete change.

[b] Southern region is the comparison group.

estimates. More educated farmers and those with better-educated spouses are more likely to adopt, the adoption-age profile shows an inverted U shape, and households with more land and more labour adopt new technologies more readily. Off-farm income is negatively associated with adoption; this variable most likely reflects effects of specialisation in agriculture. Households that are most specialised in agriculture are more likely to adopt new technologies. We used the 25th percentile of the distribution of the predicted probability of adoption as the cutoff: households with predicted probabilities greater than 42.7% were placed in the class of adopters, and others were assumed to be non-adopters. We examine the sensitivity of the results to this assumption below.

Maize research has biggest overall potential impact on poverty reduction, and has a particularly strong potential impact in the southern region (Table 6). In the south, this impact is due to the high concentration of maize production. Maize research also lowers poverty in the north and central regions by slightly more than three percentage points. Vegetable research should also reduce poverty, particularly in southern and central Malawi, where agriculture is diversified and vegetable production is common. On the other hand, even with its relatively large share of the research budget and limited acreage planted, additional funds for research on tubers and roots would not reduce poverty by much.

Table 6
Poverty headcount indices following a 50% increase in agricultural research budget by commodity, entire country and by region

Commodity	National	Region		
		Northern	Central	Southern
Maize	37.4	37.3	30.5	42.3
Roots/tubers	41.5	40.1	33.7	47.2
Groundnuts	41.4	40.3	33.5	47.2
Other legumes	41.0	40.5	33.6	46.4
Cotton	41.5	40.7	33.8	47.1
Vegetables	40.4	40.1	32.9	45.7
Rice	41.5	40.4	33.7	47.2
Sorghum/millet	41.5	40.4	33.8	47.1
Oilseeds	41.6	40.7	33.7	47.3
"BASELINE"	41.6	40.7	33.8	47.3

Note: computed using Eq. (3) with the predicted probability of adoption threshold set at the 25th percentile to re-estimate income and aggregated into the poverty headcount index. The 'BASELINE' is from Table 1. The poverty headcount index was computed using 1992/1993 NSSA data.

Maize research also reduces inequality slightly. The Gini coefficient for rural Malawi before research was 55.0 and it fell slightly to 54.2 following the forecasted income changes from increased maize research. None of the other research programs affected inequality, except for groundnut and rice research, both of which increased the Gini coefficients to 55.5 and 55.6, respectively.[8] Groundnut and rice research had virtually no effect on poverty, but increased income inequality, indicating that much of the producer benefits from these research programs will be captured by the better off farmers.

Except for maize research, measured impacts on poverty of changes in the agricultural research portfolio are relatively small. Based on 1992/1993 cropping patterns, increased research on maize would have the largest poverty-reducing impact in Malawi. Several caveats need to be noted. First, impacts for maize shown in Table 6 were derived assuming that maize research would increase productivity of all maize varieties including open-pollinated (local), composite and hybrids. In fact, only about 30% of total maize plantings are devoted to hybrids and research is likely only to increase productivity of hybrids. Second, input and pricing policies in 1992/1993 favoured maize, particularly hybrid maize, and reforms since then have diminished the profitability of maize (notably the sharp hike in fertiliser prices due to the termination of fertiliser subsidies and currency devaluation). However, maize acreage has maintained a relatively constant share in acreage planted over the past several years. Third, because maize occupies such a large part of the Malawian research portfolio, the *elasticity* of poverty reduction, or the percentage reduction in poverty given a percent increase in research expenditures, for resources devoted to maize research is likely to be small.

Except for maize, the results are not sensitive to the threshold choice for adoption probabilities. Table 7 shows the model results using a 10th and

[8] Clearly, alternative specifications could be used. For instance, if data were available, we could estimate the probability of adoption of new varieties for each crop type or the probability of adoption of any innovation that affects Eq. (2). These predicted probabilities could be used to create the $J \times J$ diagonal matrix $\mathbf{Pr}_i$. Our data set did not, however, contain information on adoption of specific seed varieties (except for hybrid maize).

Table 7
Poverty headcount indices for different adoption probability thresholds

Commodity	Percentile		
	10th	25th	50th
Maize	36.9	37.4	38.1
Roots/tubers	41.4	41.5	41.5
Groundnuts	41.2	41.4	41.3
Other legumes	41.0	41.0	41.3
Cotton	41.4	41.5	41.5
Vegetables	40.2	40.4	40.7
Rice	41.5	41.5	41.6
Sorghum/millet	41.5	41.5	41.5
Oilseeds	41.6	41.6	41.6
"BASELINE"	41.6	41.6	41.6

Note: computed using Eq. (3) with the predicted probability of adoption threshold set at different levels. The poverty headcount index was computed using 1992/1993 NSSA data.

50th percentile cutoff (households whose predicted probability of technology adoption, from the Probit model, exceeds the threshold are assumed to adopt, others do not). Obviously, the 10th percentile choice shows the strongest impact on poverty reduction, but the difference is really only noticeable for maize.

This small impact[9] of research expenditures on commodities other than maize is due to several factors. The first factor is the policy regime, discussed above, that at the time of the survey favoured maize over alternative crops. A second factor is the relatively small impact of agricultural research on incomes of households both overall and for those households below the poverty line. The predicted impact of research on incomes is shown in Table 8 and, when combined with the flatness of the cumulative income distribution function (CDF) near the poverty line, it means that agricultural research has a relatively modest impact on poverty. The flatness of the CDF is evidenced by the relatively large poverty depth index in Table 1. That is, many of the poor are far below the poverty line and relatively small increases in incomes will not remove them from the ranks of the poor.[10] In general, agricultural research will have a relatively larger impact on poverty reduction if many households or people are found right below the poverty line. This point illustrates the usefulness of computing indices such as the FGT $\alpha = 1$ and $\alpha = 2$ measures. Because the impacts on poverty are small, changes in depth and severity indices—which are even smaller—are not presented here (although these indices are straightforward to compute).[11]

The relatively small poverty- (and inequality-) reducing impact of changes in the research portfolio also results from the lack of diversification away from maize in Malawi, the small land areas planted to non-maize crops, and the high degree of dependence on off-farm income for the poorest of the poor. Additionally, although the Malawian rural poor concentrate their land into maize production, the share of maize income in total household income is still relatively small, lowering the poverty-reducing impacts of increased maize research.

As a final note, part of the reason for the small poverty impacts is caused by the relatively small percentage yield increases forecasted by the scientists. The estimated yield changes in Table 3 show surprisingly small variations across commodity programs. Clearly, these subjective judgments are subject to error. We might improve them by eliciting information about a probability distribution for expected yield changes, by reverting to historical data on yield changes, or by examining results in similar countries (see Chapter 5 in Alston et al., 1995 for a discussion).

The impact on poverty of increased research on burley tobacco is not shown in Table 6 because, as mentioned above, burley tobacco was not part of the DARTS research portfolio. The poverty indices were recomputed using an illustrative 20% predicted yield increase from a 50% increase in the tobacco research budget. As of 1992/1993, few poor smallholders grew burley tobacco. Because of this, results indicate that burley tobacco research would have had a negligible impact (not shown) on poverty. This is one instance where the change in acreage component of Eq. (1)

[9] Gini results are not presented in tables, but are available from authors upon request.

[10] 'Small' is a relative term. The estimates in Table 5 indicate that increased maize research will bring approximately 375,000 individuals out of poverty. Increased resources devoted to vegetable, other legumes, and groundnut research will reduce poverty by 108,000, 52,000 and 25,000 individuals, respectively. The 'poverty' profile can produce poverty population estimates broken down by region, and other factors.

[11] For instance, only about 16% of the rural poor and 7% of the total rural population lives in households with incomes per capita between 80 and 100% of the poverty line.

Table 8
Percentage change in household income following a 50% increase in commodity-specific research for all households and poor households

Commodity	National		Region					
			Northern		Central		Southern	
	All	Poor	All	Poor	All	Poor	All	Poor
Maize	15.2	26.3	15.2	27.2	10.2	20.4	18.8	29.0
Roots/tubers	0.4	0.6	1.9	3.2	0.2	0.2	0.2	0.4
Groundnuts	0.7	0.5	1.1	0.8	0.8	0.8	0.6	0.2
Other legumes	1.0	1.3	0.8	1.1	0.5	1.3	1.5	1.4
Cotton	0.2	0.2	0.1	0.1	0.0	0.0	0.3	0.3
Vegetables	3.2	4.3	2.1	3.1	2.5	4.4	4.1	4.4
Rice	0.7	0.2	1.6	0.4	0.2	0.1	0.8	0.3
Sorghum/millet	0.4	0.4	0.6	0.9	0.0	0.1	0.5	0.6
Oilseeds	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0

Note: computed using the forecasted yield changes from Table 3, the forecasted probability of adoption and Eq. (3).

may increase in importance. Since 1992/1993, burley production has spread dramatically even among poor smallholders, particularly in the central region. To obtain a reasonable estimate of the current poverty reduction impact of increased burley tobacco research, new household data, such as those periodically collected by the National Statistical Office (the Integrated Household Survey Program) could be used. These data would reflect post-reform cropping patterns and also contain measures of income and expenditures.

Male-headed smallholder households are less likely to be poor and extremely poor than female-headed households (see Table 9, 'before research'). Such findings are common in SSA countries. As Table 9 shows, research has a slightly different impact on each sub-group. While both sub-groups benefit most from maize and vegetable research, a slightly higher proportion of male-headed households are lifted out of poverty through this research. Maize research, in particular, reduces poverty among male-headed households by more percentage points than for female-headed households. Research on rice, roots and tubers, groundnuts, cotton and oilseeds has virtually no effect on poverty for either household headship sub-group. Gini coefficients by each sub-group are straightforward to compute.

Agricultural research alone is likely to have only a small impact on rural poverty reduction in Malawi, although there are some differential impacts by region and headship. Based on the results presented in Tables 6–9, priority areas for poverty-reducing research should be maize and vegetables, whereas crops such as roots/tubers, sorghum/millet, oilseeds, cotton have negligible poverty-reducing impacts.

The results point to some of the limitations encountered when using agricultural research to reduce poverty. Because Malawian smallholders (and those in other SSA countries) have small landholdings, depend on off-farm income, and face multiple constraints, many will be hard-pressed to directly benefit from agricultural research. The poverty problems faced by

Table 9
Poverty indices by household headship following research-generated productivity gains

Commodity	Male-headed		Female-headed	
	Poverty	Extreme poverty	Poverty	Extreme poverty
Before research	36.6	19.4	52.3	28.0
After research on				
Maize	33.1	17.0	46.6	24.0
Roots/tubers	36.5	19.3	52.1	27.9
Groundnuts	36.4	19.3	52.1	27.7
Other legumes	36.2	19.1	51.3	27.4
Cotton	36.4	19.3	52.3	28.0
Vegetables	35.7	18.8	50.4	27.0
Rice	36.5	19.4	52.1	28.0
Sorghum/millet	36.4	19.3	52.2	27.9
Oilseeds	36.6	19.4	52.3	28.0

Note: 'poverty' refers to the headcount (proportion) of households below the upper poverty line, and 'extreme poverty' is the headcount below a lower line. See World Bank (1996) for information on the poverty lines use.

a large proportion of Malawi's smallholder population require a broader rural research and extension strategy, in combination with policy reforms, and instruments to enhance smallholders' meager asset bases (Alwang and Siegel, 1999; Rukuni et al., 1998). In order to more accurately measure the impact of research on smallholders, however, labour and commodity market effects need to be modelled. This method can be extended to incorporate indirect effects in broader modelling efforts.

6. Concluding remarks

The method presented in this paper can help provide a basis for improving the dialogue between policymakers and agricultural research managers in priority-setting exercises. In contrast to widely used economic surplus methods, the proposed method has the advantage that it is consistent with commonly used measures of poverty. The poverty measures represent an alternative means of adding up economic surplus, and provide another dimension to the decision making process because changes in economic surplus, historical studies on rates of return on research, and impacts on poverty can be considered during research planning and priority-setting exercises.

The major strength of the method is that it produces measures that are common 'language' in national poverty debates. Also, the method can be applied with relative ease in an ex ante priority-setting exercise using agricultural household survey data. There is a great deal of flexibility with these poverty measures, for example when partitioning sub-groups and comparing impacts on poverty and inequality among different sub-groups. In the example we disaggregated the sample of households by region and headship. It is also possible to disaggregate the sample by, for example 'remoteness' based on distance from markets, rather than by a broadly defined 'region' (where not all households might be remote).

Although the method can be implemented with relative ease, the baseline data (e.g. cropping patterns and prices) generate a bias, especially in countries undergoing reforms and economic adjustment. A weakness of the model, like many economic surplus measurement techniques, is that it reinforces existing (at the time of data collection) policy biases. In the case of Malawi, policies in the early 1990s were biased toward smallholder maize production, and cropping patterns reflected this fact. Following price and market reforms, the relative profitability of different crops have changed dramatically. Due to adoption lags, however, the full impact of policy reversals is not yet evident in cropping patterns and yield data. Thus, there is a need for updating the household survey data.

When households obtain a significant percentage of income from off-farm sources there is need for additional work, since the method as presented does not account for factor and product market effects that result from technical change. To estimate these impacts, more detailed modelling is required. Changes, for example in product prices, would affect incomes, the cost of living, and the position of the poverty line. If the data set contains details on consumption expenditures, the impact of supply shifts resulting from technical change could be reflected through changes in the cost of living.

Extensions to the method could involve more detailed modelling of production and consumption decisions under different policy regimes. These models could be used to understand the probability and intensity of adoption, impacts of technology on cropping patterns, off-farm employment, etc. The results of these models could be used to predict the effects of different research portfolios on aggregate measures of poverty. Multi-market or computable general equilibrium models could be used to generate forecasts of price changes and to capture labour market effects. In all cases, it is useful to return to the primary data to examine changes in indices of poverty.

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