ELSEVIER

Journal of Development Economics 77 (2005) 53–73

JOURNAL OF Development ECONOMICS

www.elsevier.com/locate/econbase

Poverty-dominant program reforms: the role of targeting and allocation rules

Jean-Yves Duclos[a,1], Paul Makdissi[b,*], Quentin Wodon[c]

[a] *CIRPÉE, Département d'économique, Pavillon De Sève, Université Laval, Sainte-Foy, Québec, Canada G1K 7P4*

[b] *Département d'économique and GRÉDI, Université de Sherbrooke, 2500 boulevard de l'Université, Sherbrooke, Québec, Canada J1K 2R1*

[c] *LCSPR, World Bank, 1818 H Street, NW, Washington, DC 20433, USA*

Received 1 April 2003; accepted 1 March 2004

Abstract

We propose simple graphical methods to identify poverty-reducing marginal reforms of transfer programs. The methods are based on Program Dominance curves that display cumulative program benefits weighted by powers of poverty gaps. These curves can be decomposed simply as sums of targeting dominance curves and allocation dominance ones, and can serve to verify whether the assessment of marginal program reforms is sensitive to the choice of poverty lines and poverty measures as well as to differences across programs in revenue sources and incentive effects.

JEL classification: D31; D63; H22; H53; I32; I38
Keywords: Poverty; Targeting; Public policy; Stochastic dominance

1. Introduction

Governments in developed and developing countries try helping the poor in many different ways. Traditional poverty alleviation programs include *inter alia* consumption

* Corresponding author. Tel.: +1 819 821 8000; fax: +1 819 821 7237.
E-mail addresses: jyves@ecn.ulaval.ca (J.-Y. Duclos), paul.makdissi@USherbrooke.ca (P. Makdissi), qwodon@worldbank.org (Q. Wodon).
[1] Tel.: +1 418 656 7096; fax: +1 418 656 7798.

0304-3878/$ - see front matter
doi:10.1016/j.jdeveco.2004.03.001

subsidies (for example, on food, public utilities or transportation) and low-wage public works or other forms of relief for the unemployed. In Latin America and other regions, more recent "smart" transfers include stipends for poor children conditional on school attendance (e.g., Skoufias, 2001). These transfers are said to be smart because, beyond their immediate impact on poverty, they are supposed to help achieve long-term poverty reduction through a positive impact on human capital (by the conditionality component). Even programs which are not explicitly designed to alleviate poverty may have significant impacts on the poor, and should therefore be taken into account in an overall poverty reduction strategy.

To estimate the impact of such programs on poverty and to suggest reforms to them, analysts often either resort to a comparison of some summary poverty measures with and without the programs, or analyze the programs' "targeting errors" and how they vary with program reforms.[2] A weakness of both approaches is their sensitivity to the choice of (necessarily somewhat) arbitrary poverty lines and of peculiar value judgements regarding the social welfare objectives of the government—for instance, that the government cares equally for all the poor, regardless of how far from the poverty line they may be.[3] For instance, the analysis of targeting errors focuses typically on sharp 0/1 indicators, and arguably tends to differentiate too drastically between the poor and the non poor, in particular between those in similar circumstances but who just happen to lie on opposite sides of some poverty line.

Other difficulties in the assessment of program changes come from their differential effects on average deadweight losses. Such differential effects can occur when the programs are funded from different revenue sources: differences in the cost of public funds that arise from differences in those revenue sources must then be taken into account (see for instance Slemrod and Yitzhaki, 1996). Differences in the effects on average deadweight losses can also arise from the differential behavioral changes that different program reforms can generate among program beneficiaries. These differential behavioral changes can in general also affect the direct disaggregated welfare impact of program reforms.

The tools developed in this paper can help alleviate many of the above concerns. To do this, the paper builds on the stochastic dominance literature and further focuses on the analysis of *marginal* program reforms. One practical justification for this focus is that actual changes in tax and benefit systems are indeed typically "slow and piecemeal" (see for instance Feldstein, 1975), and that existing tax and benefit systems are thus natural departure points for the identification of directions for desirable program reforms. A most important practical advantage of focussing on marginal program changes, however, is that evaluating their welfare impact does not require estimates of individual demand and supply functions, and does not depend either on whether such reforms induce individual behavioral changes. The distributional welfare

[2] See for instance Baker and Grosch (1994), Cornia and Stewart (1995), Ravallion and Datt (1995), Grosch (1995), and Wodon (1997). The targeting errors are variably called "leakage" and "undercoverage" errors, "E" and "F" mistakes, and "Type I" and "Type II" errors.

[3] For a discussion of this, see Atkinson (1987), Foster and Shorrocks (1988a,b,c), Jenkins and Lambert (1997), Ravallion (1994) and Zheng (1999, 2000a), among many others.

impact of such program changes can instead be assessed directly from observed pre-reform behavior alone.[4] This simplifies greatly the analysis, as we will see.

The simple graphical methods that we propose can then make the assessment of program reforms *robust* to the choice of poverty lines and poverty measures as well as to differences in revenue sources and behavioral impacts across program reforms. Program reforms that decrease poverty "robustly" will be called "poverty dominant", in direct reference to the usual stochastic dominance literature.

The graphical methods are based on Program Dominance (PD) curves. PD curves are similar in spirit to the Consumption Dominance curves proposed by Makdissi and Wodon (2002) and Duclos et al. (2002) for the analysis of indirect tax reforms. The main difference between these tools is that PD curves measure the poverty impact of marginal variations in program benefits (and taxes), whereas Consumption Dominance curves capture the poverty impact of marginal price changes.

First-order PD curves show the share in total program benefits of those individuals at a given income level. Second-order PD curves indicate the cumulative share of total program benefits of those with income below a given threshold. Higher-order PD curves weight program benefits by increasingly higher powers of poverty gaps. Increasing expenditures on program k and decreasing expenditures on program l is poverty dominant for all poverty lines up to some z^+ and for all poverty indices of a given ethical order if the PD curve of that order for program k is higher than the PD curve for program l at every threshold under z^+. In addition to being useful for normative and policy purposes, PD curves thus also display rich and useful descriptive program information.

A useful interpretive and analytical contribution of the paper consists in decomposing the PD curve of any given program into targeting and allocation components. As recently noted by Coady and Skoufias (2001) and Wodon and Yitzhaki (2002) in the context of social welfare and inequality analysis respectively, a program's "good" impact can be due to good targeting (i.e., the poor are more likely to benefit than the non-poor), as well as to a good allocation of benefits among program participants (poorer individuals among participants receive larger benefits)—or both. We show that a PD curve can be decomposed simply into the sum of a targeting dominance (TD) curve–which only takes into account who benefits or not from the program–and an allocation dominance (AD) curve–which captures differences in benefit allocations among program beneficiaries.[5]

While examination of PD curves may suggest that one program dominates a second, that second program may well dominate the first from a targeting point of view, as revealed by a comparison of their TD curves, or from an allocation point of view, as

[4] See, among many others, Ahmad and Stern (1984, 1991), Besley and Kanbur (1988), Yitzhaki and Slemrod (1991), and Mayshar and Yitzhaki (1995).

[5] The idea of decomposing poverty differences into components is not new. It has been applied, for instance, to sectoral decomposition by Ravallion and Huppi (1991) and to growth/redistribution by Datt and Ravallion (1992)—see also Shorrocks (1999) for a generalized decomposition method based on Shapley's (1954) work. As should become clear later on, our own *TD* term differs somewhat in spirit from Datt and Ravallion's growth term since *TD* captures the impact of an increase in income for only a part of the population—that of existing benefit recipients.

revealed by a comparison of their AD curves. Although program reforms would usually be implemented on the basis of the comparison of their PD curves, the information provided by the TD and AD curves enables detecting the effect of targeting and allocation rules on the overall performance of various programs.

For example, "bad" targeting may be intentional to gain middle class political support for a given program. In such a case, however, a progressive allocation mechanism among program participants may still make an extension of the program desirable. By contrast, a program may target a specific group whose members tend on average to be poor, but the allocation mechanism may be so much in favor of the richer members of that group that the program overall is not poverty dominant. Combining information on the overall as well as on the targeting and allocation impacts may thus be very useful to suggest reforms to improve program performance.

We also use the properties of the PD curves to estimate the critical poverty line up to which a program reform can be considered to be poverty dominant at a given order of dominance. We further suggest how the taxation mechanisms implicit in the various programs, as well as their incentive and economic efficiency effects, may affect whether a program reform can be said to be poverty dominant or not.

An alternative to the comparison of the PD, TD and AD curves is to compare the usual stochastic dominance curves (*viz*, cumulative distribution functions or their integrals) for the pre- and post-reform distributions of well-being. Comparing stochastic dominance curves is indeed more general since it can take into account the impact of behavioral changes on disaggregated welfare. For marginal program reforms, the two approaches technically yield identical results. Comparing distributions of well-being under marginal program reforms is, however, more conveniently done using the PD and associated curves since the stochastic dominance curves are then (at the limit) impossible to distinguish and since this paper's curves provide independently useful normative and descriptive information on how the programs work.

We illustrate the methods with a comparison of two Mexican programs. The first is called PROCAMPO, a cash transfer for farmers designed to facilitate the transition to a rural market economy. The program was created in 1994 to offset the potentially negative impact of the termination of farming support programs (within the broader context of the liberalization of the Mexican agriculture agreed upon as part of the North American Free Trade Agreement). PROCAMPO transfers are given to eligible producers of basic crops on a per hectare basis. The second program is Liconsa (Leche Industrializada Conasupo). It provides milk subsidies for qualifying families. To qualify, families must earn less than two minimum wages and have children under the age of 12. Comparing TD curves reveals that PROCAMPO is better targeted than Liconsa. However, when allocation effects (the AD curves) are taken into account, the resulting comparison of the PD curves suggests that it would be poverty dominant to expand Liconsa and to reduce funding for PROCAMPO. This conclusion could nevertheless be sensitive to differences in the relative economic efficiency of the two programs.

The rest of the paper proceeds as follows. Section 2 develops the analytical framework, Section 3 presents the empirical illustration, and Section 4 concludes.

2. The framework

2.1. Program reforms

Following King (1983), let y be pre-reform real income assessed using pre-reform prices as reference prices. y is a money-metric indicator of welfare: in King's terminology, it is also called "equivalent" income.[6] For expositional simplicity, we refer to y simply as income. Poverty is assessed on the basis of the distribution of these individual incomes, and transfer programs add to them. An existing program k transfers an average monetary amount $t_k(y)$ per beneficiary of income y. The proportion of the population at income y that benefits from the program is given by $\tau_k(y)$. Working in a continuous setting, let $F(y)$ be the cumulative density function of y, let $f(y)$ be its derivative, the density of income at y, and let incomes range between 0 and a. A "targeting function" can then be defined as

$$\phi_k(y) = \tau_k(y) \cdot f(y). \tag{1}$$

$\Phi_k = \int_0^a \phi_k(y)\mathrm{d}y \leq 1$ denotes the overall share of the population that benefits from the program. The cumulative distribution function $G_k(y)$ of benefit recipients is given by

$$G_k(y) = \frac{\int_0^y \phi_k(x)\mathrm{d}x}{\Phi_k}, \tag{2}$$

and the density of recipients is then

$$g_k(y) = \frac{\mathrm{d}G_k(y)}{\mathrm{d}y} = \frac{\phi_k(y)}{\Phi_k}. \tag{3}$$

Program k's mean transfer across the population is given by

$$T_k = \int_0^a t_k(y)\phi_k(y)\mathrm{d}y, \tag{4}$$

although the average transfer *among* program k's beneficiaries equals

$$\bar{t}_k = \frac{T_k}{\Phi_k} = \int_0^a t_k(y)g_k(y)dy. \tag{5}$$

To identify poverty-dominant program reforms and to assess the targeting and allocation efficiency of alternative programs and program reforms, we will consider (marginal) proportional changes in the initial transfer schedules[7]. An agent at income y

[6] As noted by King, the concept of equivalent income function is also used by McKenzie (1956), Samuelson (1974) and Varian (1980).

[7] Note that this "homogeneity" property for program reforms is more general than it may appear. Think for instance of a reform to Mexico's Liconsa, as we will simulate later on in the paper. We can envisage a reform that increases everyone's Liconsa subsidy by the same proportion, or alternatively one that increases the subsidy of only a subpopulation of Liconsa's recipients. We can also think of a reform that increases by different proportions the Liconsa subsidies of different subpopulations. Although, for expositional simplicity, we do not consider explicitly such combinations in the paper, they can be easily accommodated for by suitably re-defining t_k and $t_k\Delta t_k$. Note also that the impact of such kinds of reforms is similar to that of price reforms: proportional changes in individual welfare also occur then.

who is already in receipt of a transfer $t_k(y)$ will thus see his income increase by $t_k(y)\ \Delta t_k$ following the reform.[8] Those not already in receipt of the transfer will not be affected by this marginal reform. The impact of such a reform can then be decomposed into targeting and allocation components as follows:

$$t_k(y)\Delta t_k = \underbrace{\bar{t}_k \Delta t_k}_{\text{Targeting}} + \underbrace{(t_k(y) - \bar{t}_k)\Delta t_k}_{\text{Allocation}}. \tag{6}$$

The reform $t_k(y)\Delta t_k$ has the effect of keeping unchanged the relative distribution of benefits $t_k(y)$, since everyone's benefit is increased by the same proportion. The targeting component assigns the *same absolute* marginal benefit to all existing recipients. The allocation component adds marginally to benefits among recipients in proportion to the difference between existing individual and mean allocation.

To describe in greater details the distributive impact of these various components, note that a concentration index of benefits among recipients can be expressed as (see for instance Rao, 1969)

$$I_k = 2 \cdot \int_0^a \frac{\bar{t}_k - t_k(y)}{\bar{t}_k} (1 - G_k(y)) \mathrm{d}G_k(y). \tag{7}$$

Since $\int_0^a t_k(y)\mathrm{d}G_k(y) = \bar{t}_k$, it is easy to show that Eq. (7) can usefully be rewritten as

$$I_k = \frac{2\mathrm{cov}(t_k(y), G_k(y))}{\bar{t}_k}. \tag{8}$$

Ceteris paribus, the lower the value of I_k, the more progressive (and the more "pro-poor") is the benefit k-for a discussion, see Kakwani (1977) and Pfähler (1987) for instance. There also exists an interesting link between I_k and the "Gini Income Elasticity" that is widely used in the evaluation of programs[9]: I_k is the numerator in that elasticity. Since the denominator is identical to all programs, ranking programs according to I_k is identical to ranking programs according to the Gini income elasticities.

Using (6) and (7), it follows that the proportional reform $t_k(y)\Delta t_k$ has no impact on the program's concentration of benefits within its beneficiaries, since it increases $t_k(y)$ and $\bar{t}_k$ by the same proportion. The mean transfer increases, however, by $\bar{t}_k \Delta t_k$.

The mean effect of the allocation component in (6) is nil, since

$$\int_0^a (t_k(y) - \bar{t}_k)\Delta t_k \mathrm{d}F(y) = (\bar{t}_k - \bar{t}_k)\Phi_k \Delta t_k = 0. \tag{9}$$

The allocation component therefore involves a pure redistribution of benefits among recipients. It has the simple impact of spreading benefits away from their mean by a proportional factor Δt_k. As can be checked from (7), this changes the concentration index by $I_k \Delta t_k$. If the concentration index was negative initially (corresponding to a progressive benefit) it makes it even more progressive, and if it was regressive initially

[8] By the envelope theorem, this is regardless of whether he changes his behavior following the reform. This is because income here equals money-metric welfare and not nominal income.

[9] See Wodon and Yitzhaki (2002) for a survey.

(corresponding to a positive concentration index), then the allocation effect increases its regressivity among benefit recipients.

As for the targeting component in (6), it changes mean transfers by $\bar{t}_k \Delta t_k$. Being the same in absolute value for all beneficiaries, this targeting impact equalizes the distribution of transfers among recipients. As can be checked from (6) and (7), it changes I_k by $-I_k \Delta t_k/(1+\Delta t_k)$, and thus moves the original concentration of benefits among recipients towards 0. If the concentration index was negative (i.e, progressive) initially among recipients, the targeting effect makes it less progressive, and if the benefit was regressive initially, the targeting effect makes it less so.

2.2. Poverty impact

Next, to assess the impact of a marginal program reform on poverty, we follow much of the literature and focus for simplicity on additive poverty indices. Let $P(z)$ be such an additive poverty index. It can be expressed as:

$$P(z) = \int_0^a p(y,z)\mathrm{d}F(y), \tag{10}$$

where z is the poverty line and $p(y,z)$ is the contribution to total poverty of an individual with income y. Now consider the classes $\Pi^s(z)$ of poverty indices $P(z)\in\Pi^s(z)$ with

$$\Pi^s(z) = \left\{ P(z) \middle| \begin{array}{l} p(y,z) = 0 \text{ if } y>z, p(y,z)\in\hat{C}^s(z), \\ (-1)^i p^{(i)}(y,z)\geq 0 \text{ for } i = 0, 1\ldots, s, \\ p^{(t)}(z,z) = 0 \text{ for } t = 0, 1, \ldots, s-2 \text{ when } s\geq 2, \end{array} \right\} \tag{11}$$

where $\hat{C}^s(z)$ is the set of continuous functions which are s-time piecewise differentiable over $[0, z]$, and where the superscript $^{(s)}$ stands for the s-th order derivative with respect to y. The $\hat{C}^s(z)$ continuity assumption is used for analytical simplicity.[10]

When s=1, poverty indices weakly decrease ($p^{(1)}(y,z)\leq 0$) when an individual's income increases. These indices are thus "Paretian": increasing anyone's income cannot be bad for poverty. They are also symmetric: interchanging any two individuals' incomes leaves unchanged the poverty indices. Poverty indices within $\Pi^2(z)$ are also convex and must thus respect the Pigou-Dalton principle of transfers: a mean-preserving

[10] This continuity could be relaxed to include indices whose $(s-1)$th derivative is discontinuous and which are therefore not s-time piecewise differentiable. It would also be possible to include non-additive poverty indices (such as the Thon (1979)–Chakravarty (1983)–Shorrocks (1995) poverty index) within a more general framework. Note that, as Zheng (1999) and others have discussed, moving beyond s=2 restricts poverty indices to be continuous at the poverty line (see the last line of (11)), and thus to be "FGT-like"—see (12) just below. An alternative approach would be to impose a minimum-sensitivity requirement on poverty measures, which can also enhance the power of poverty rankings, as shown in Zheng (2000b). We do not pursue this avenue here but leave it instead for future work.

transfer of income from a higher-income person to a lower-income one weakly decreases poverty. The $\Pi^2(z)$ indices are often said to be "distribution-sensitive" poverty indices. The poverty indices that belong to $\Pi^3(z)$ must also be sensitive to favorable composite transfers, namely, that a beneficial Pigou-Dalton transfer within the lower part of the distribution, accompanied by an adverse Pigou-Dalton transfer within a higher part of the distribution, must weakly reduce poverty, provided that the variance of the distribution is not increased. The interpretation of higher-order classes of indices follows analogously.[11]

A particular subclass of additive poverty indices is found in Foster et al. (1984). It is defined for $\alpha \geq 0$ by

$$\mathrm{FGT}_F^{\alpha}(z) = \int_0^z \left(\frac{z-y}{z}\right)^{\alpha} \mathrm{d}F(y). \tag{12}$$

$\mathrm{FGT}^0(z)$ gives the most widely used index of poverty, the so-called poverty headcount, and $\mathrm{FGT}^1(z)$ yields the (normalized) average poverty gap. Note that $\mathrm{FGT}^{\alpha}(z)$ belongs to $\Pi^s(z)$ for $\alpha \geq s-1$.

The impact on the FGT indices of a marginal proportional increase of Δt_k in the resources allocated to program k can be shown to be given by

$$\frac{\partial \mathrm{FGT}^{\alpha}(z)}{\partial t_k} = \begin{cases} -\, t_k(z)\phi_k(z) & \text{if } \alpha = 0 \\ -\, \alpha z^{-\alpha} \displaystyle\int_0^z t_k(y)(z-y)^{\alpha-1}\phi_k(y)\mathrm{d}y & \text{if } \alpha > 0. \end{cases} \tag{13}$$

This impact depends on the targeting function $\phi_k(y)$, on the allocation of transfers underneath z, and on the distribution of poverty gaps z–y.

The poverty impact in (13) can also be decomposed into a targeting and an allocation component. Using (6), the targeting component is given by

$$\left.\frac{\partial \mathrm{FGT}^{\alpha}(z)}{\partial t_k}\right|_T = \begin{cases} -\, \bar{t}_k\phi_k(z) & \text{if } \alpha = 0 \\ -\, \alpha z^{-\alpha} \displaystyle\int_0^z (z-y)^{\alpha-1}\bar{t}_k\phi_k(y)\mathrm{d}y & \text{if } \alpha > 0. \end{cases} \tag{14}$$

Note that (14) has a structure somewhat similar to $\mathrm{FGT}^{\alpha-1}(z)$, as noted by Besley and Kanbur (1988) among others. The allocation component is given by

$$\left.\frac{\partial \mathrm{FGT}^{\alpha}(z)}{\partial t_k}\right|_A = \begin{cases} -\, (t_k(z)-\bar{t}_k)\phi_k(z) & \text{if } \alpha = 0 \\ -\, \alpha z^{-\alpha} \displaystyle\int_0^z (t_k(y)-\bar{t}_k)(z-y)^{\alpha-1}\phi_k(y)\mathrm{d}y & \text{if } \alpha > 0. \end{cases} \tag{15}$$

These distinctions allow comparisons of the impact of three types of program changes:

- the poverty impact of a "proportional" program change that increases all transfers by the same proportion, thus maintaining intact the relative distribution (and the concentration index) of transfers among existing recipients (Eq. (13));

[11] For more details, see Duclos et al. (2002).

- the poverty impact of a "lump-sum" program change that increases all transfers by the same absolute amount, maintaining unchanged the population of recipients (Eq. (14));
- and the poverty impact of an "allocative" program change that leaves unchanged the mean transfer that is distributed, but that increases by the same proportion Δt_k for all recipients their benefit's spread from that mean transfer, thus changing proportionately by Δt_k the transfer's concentration index among recipients (Eq. (15)).

2.3. Budgetary impact

Now consider a marginal program reform that reduces marginally the resources devoted to program l in order to increase marginally the resources allocated to program k. If the programs are funded through identical sources and if they do not induce behavioral reactions on the part of economic agents, then the cost to the government of increasing individual income on average by \$1 is the same regardless of the program. However, programs may be funded through different means of taxation. They may also induce different behavioral responses on the part of their beneficiaries, especially (but not uniquely) if conditionalities are involved. In both cases, there can exist differential economic efficiency costs to raising individual incomes.

In order to take these factors into account, we need to evaluate the impact of marginal program reforms on the government budget. Let us denote by B this budget. The impact of a proposed program reform on the budget is given by

$$\mathrm{d}B = \frac{\partial B}{\partial t_k}\Delta t_k + \frac{\partial B}{\partial t_l}\Delta t_l. \tag{16}$$

Assuming budget neutrality, we have $\mathrm{d}B$=0, and we may define an economic efficiency ratio γ for additional expenditures on the two programs as

$$\gamma = \frac{(\partial B/\partial t_k)/T_k}{(\partial B/\partial t_l)/T_l}. \tag{17}$$

The numerator in (17) gives the cost in government resources per dollar of increase in *per capita* income that is generated by reforming program k. The denominator gives the same indicator for a reform of program l.

The definition of γ implicitly takes into account potential differences in the marginal cost of financing the two programs as well as potential differences in their behavioral impacts. If, for instance, running program k is proportionately more costly administratively than running l, then γ will exceed 1. If the revenue source used for financing program k is less economically efficient than that for financing program l–because the deadweight loss and the economic distortions of using k's source of finance are larger—then again γ will exceed 1. If program l is better designed to induce benefit recipients to decrease less their labor supply or other tax-generating activities, or to increase less their subsidized activities, then program l will be more efficient in generating increases in net income, and γ will again exceed 1.

2.4. Poverty-dominant program reforms

Now, the ranking of the above program reforms may also well be contingent on the particular choice of a poverty line and of a poverty index. An important purpose of this paper is to identify program reforms that are poverty dominant—in the sense of necessarily decreasing poverty for all poverty indices $P(z) \in \Pi^s(z)$ and for all poverty lines up to some z^+. To do this, use (13) and define the program dominance curve for program k as $\mathrm{PD}_k^s(z)$:

$$\mathrm{PD}_k^s(z) = -T_k^{-1} \frac{\partial \mathrm{FGT}^{s-1}(z)}{\partial t_k} \tag{18}$$

$$= \begin{cases} \dfrac{t_k(z)}{\bar{t}_k} g_k(z) & \text{if } s = 1 \\ (s-1) z^{1-s} \displaystyle\int_0^z (z-y)^{s-2} \frac{t_k(y)}{\bar{t}_k} g_k(y) \mathrm{d}y & \text{if } s > 1. \end{cases} \tag{19}$$

Note that $\mathrm{PD}_k^1(z)$ is the density of public spending on program k that is spent on individuals with income z. $\mathrm{PD}_k^2(z)$ gives the cumulative share of public spending on program k that is spent on individuals with income z or less.[12] As we will see in the illustration, this provides valuable descriptive information on the distribution of transfers. Note also that $\mathrm{PD}_k^2(z)$ is a variant of the usual concentration curve, the only difference being that $\mathrm{PD}_k^2(z)$ is a function of z and that the concentration curve is a function of $F(z)$. For $s \geq 3$, these shares are weighted by a power of the poverty gap which is increasing with s.

This leads to the following result (proofs appear in Appendix A).

Proposition 1. *A revenue-neutral marginal policy reform that increases proportionately all transfers under program k and reduces proportionately all those under program l will reduce poverty for all poverty indices $P(z) \in \Pi^s(z)$ and for all poverty lines $z \in [0, z^+]$ if and only if*

$$\mathrm{PD}_k^s(y) - \gamma \mathrm{PD}_l^s(y) \geq 0 \quad \text{for all } y \in [0, z^+]. \tag{20}$$

For $s=1$ and assuming $\gamma=1$, condition (20) means that the share of public spending on program k that is directed to individuals with income y must be higher than the share of the public spending on program l directed to the same individuals, and this must be the case at every income level lower than z^+. For $s=2$ and $\gamma=1$, condition (20) implies that the cumulative share of spending on program k that is directed to individuals with income y or less must be higher than the corresponding cumulative share for program l, again for every income level lower than z^+. Whatever the ethical order of the classes of poverty indices, we need to assess whether the PD curve for a program k is higher than that for a program l, and this, at all income levels up to z^+. If this is so, it is poverty dominant to inject proportionately more resources into program k at the expense of program l.

[12] Assuming that, for expositional clarity, we normalize $\mathrm{PD}_k^2(z)$ by $1/z$. This, we do implicitly throughout the paper for all second-order dominance curves.

To assess the impact of a "lump-sum" marginal program reform, we use (14) and define a targeting dominance curve as:

$$TD_k^s(z) = -T_k^{-1}\frac{\partial \mathrm{FGT}^{s-1}(z)}{\partial t_k}\bigg|_T \tag{21}$$

$$= \begin{cases} g_k(z) & \text{if } s=1 \\ (s-1)z^{1-s}\int_0^z (z-y)^{s-2} g_k(y)\mathrm{d}y & \text{if } s>1. \end{cases} \tag{22}$$

$\mathrm{TD}_k^1(z)$ represents the density of program beneficiaries at income z. $\mathrm{TD}_k^2(z)$ shows the proportion of the population of beneficiaries who have income z or less. For higher s, $\mathrm{TD}_k^s(z)$ is simply a linear transformation of the $\mathrm{FGT}_{Gk}^{s-2}(z)$ index (the index of those who benefit from the program k).

A program's targeting rule can be deemed good and will thus provide a good basis for a poverty-dominant lump-sum program reform

- if, for s=1, the program focuses on those who are just below the poverty line (large $g_k(z)$ in (22)),
- or if, for s>1, the program is such that $(z-y)^{s-2}g_k(y)$ in (22) is large on average, *viz*, that the $\mathrm{FGT}_{G_k}^{s-2}(z)$ index is large.

This leads to the following result.

Proposition 2. *A revenue-neutral "lump-sum" marginal policy reform that increases by the same amount the income of all recipients of program k and decreases by the same amount the income of all recipients of program l will decrease poverty for all poverty indices $P(z)\in\Pi^s(z)$ and for all poverty lines $z\in[0,z^+]$ if and only if*

$$TD_k^s(y) - \gamma TD_l^s(y) \geq 0 \quad \text{for all } y\in[0,z^+]. \tag{23}$$

We may also wish to determine whether a single program's revenue-neutral allocative reform would be poverty dominant. For this, and using (15), define the following allocation dominance curve:

$$AD_k^s(z) = -T_k^{-1}\frac{\partial \mathrm{FGT}^{s-1}(z)}{\partial t_k}\bigg|_A \tag{24}$$

$$= \begin{cases} \dfrac{t_k(z)-\bar{t}_k}{\bar{t}_k} g_k(z) & \text{if } s=1 \\ (s-1)z^{1-s}\displaystyle\int_0^z \frac{t_k(y)-\bar{t}_k}{\bar{t}_k}(z-y)^{s-2} g_k(y)\mathrm{d}y & \text{if } s>1. \end{cases} \tag{25}$$

Recall that an allocative reform increases by $I_k\Delta t_k$ the concentration index I_k of transfers. This reallocation of the benefits of a program k will tend to be poverty dominant if those just below the poverty line receive currently more than their share of the benefit (for s=1) and would therefore benefit from a spread-increasing reform, or if there is a positive correlation between the spreads $(t_k(y)-\bar{t}_k)$ and the poverty contributions $(z-y)^{s-2}g_k(y)$ (for other values of s).

Proposition 3. *A marginal reform of program k that increases proportionately the spread of all transfers from their mean value will decrease poverty for all poverty indices $P(z)\in\Pi^s(z)$ and for all poverty lines $z\in[0,z^+]$ if and only if*

$$AD_k^s(y)\geq 0 \quad \text{for all } y\in[0,z^+]. \tag{26}$$

For any order of poverty dominance, $\mathrm{AD}_k^s(y)$ is simply the difference between $\mathrm{PD}_k^s(y)$ and $\mathrm{TD}_k^s(y)$. $\mathrm{AD}_k^s(y)$ may thus be interpreted as the gain (or the loss) in poverty reduction that is caused by existing allocation rules following a proportional program reform. Hence:

Proposition 4. *A revenue-neutral marginal policy reform that increases proportionately all transfers under program k and reduces proportionately all transfers under program l will improve allocation for all poverty indices $P(z)\in\Pi^s(z)$ and for all poverty lines $z\in[0,z^+]$ if and only if*

$$AD_k^s(y)-\gamma AD_l^s(y)\geq 0 \quad \text{for all } y\in[0,z^+]. \tag{27}$$

Note that the results of Propositions 1, 2, 3 and 4 can be extended to non-additive poverty indices for s=1,2, as well as to social welfare indices by fixing $z^+=a$. Non-additive first-order indices must be symmetric and non-increasing (non-decreasing, for social welfare indices) in individual income, and second-order indices must further be Schur-convex (Schur-concave, for social welfare indices).

Note also that it may be the case that political factors and constraints impose in practice a particular shape on program reforms, as suggested for instance in an interesting paper by Lanjouw and Ravallion (1999). One way to allow for this in our own framework would be to make $\tau_k(y)$ dependent on the level of T_k. Estimating or specifying a function $\tau_k(y,T_k)$ could then lead to a straightforward extension of the above results.

2.5. Bounds to poverty dominance

Whether one wishes to analyze overall program, targeting or allocation dominance, if the relevant dominance tests fail over an initial range of poverty lines $z\in[0,z^+]$, two different routes may be followed. One may increase the order of dominance until a robust assessment is obtained over the initially specified range $[0,z^+]$. One may alternatively estimate an upper critical bound z^s for a range $[0,z^s]$ of poverty lines that does not quite extend to z^+. The critical poverty lines z_P^s, z_T^s, z_A^s and z_{AR}^s beyond which conditions (20), (23), (26) and (27) do not hold anymore are given respectively by

$$z_P^s=\sup\left\{z: PD_k^s(y)-\gamma PD_l^s(y)\geq 0, \quad y\in[0,z]\right\}, \tag{28}$$

$$z_T^s=\sup\left\{z: TD_k^s(y)-\gamma TD_l^s(y)\geq 0, \quad y\in[0,z]\right\}, \tag{29}$$

$$z_A^s = \sup\{z : AD_k^s(y) \geq 0, \quad y \in [0, z]\}, \tag{30}$$

and

$$z_{AR}^s = \sup\{z : AD_k^s(y) - \gamma AD_l^s(y) \geq 0, \quad y \in [0, z]\}. \tag{31}$$

Estimators $\hat{z}^s$ of these critical values are given by replacing the population distribution with the sampling one. Their use will be illustrated in the next section.

3. Empirical illustration

3.1. Mexican programs and data

We now apply the above tools to an illustrative analysis of the impact of a balanced-budget reform involving two Mexican transfer programs. The first program, the "Program of Direct Payments to the Countryside" (PROCAMPO), is an income-support program for agricultural producers started in 1993/94. As noted by Cord and Wodon (2001), the program aims to ease the transition towards a market economy and specifically to facilitate the agricultural sector's adjustment to the removal of guaranteed prices and market support for key grains and oilseeds. It provides agricultural producers (those with the legal usufruct rights over the land) with a fixed payment per hectare that is not linked to current production trends. The number of eligible hectares per producer is the number of hectares the producer had devoted to the production of one of the nine PROCAMPO crops (maize, beans, wheat, cotton, soybeans, sorghum, rice, barley, safflower and barley) in one of the three agricultural cycles preceding August 1993. The payments are made per hectare for each crop season and, for greater transparency, are fixed at the same level across the country. PROCAMPO is a transitional program expected to terminate in 2008.

The second program is Liconsa (Leche Industrializada Conasupo). Qualifying families can purchase from 8 to 24 litres of milk per week at a discount of roughly 25% off the market price. To qualify, families must earn less than two minimum wages and have children under 12. The ration of milk is determined by the number of children under the age of 12 (8 l for families with one or two children, 12 litres for three children, and 24 litres for 4 children or more). About 5.1 million children benefit from such subsidies.

This illustration uses household level data from the 1997 ENCASEH survey conducted by the staff of PROGRESA, a large Government agency. The survey covers most areas of the countries and it has detailed information on program participation.

3.2. First-order poverty dominance

Fig. 1 provides estimates of the $PD^1(z)$, $TD^1(z)$, and $AD^1(z)$ curves for different values of z. *Per capita* incomes on the horizontal axis have been normalized by regional poverty lines so that cost-of-living differences between urban and rural areas are taken into account. A value of one indicates that a household is at the level of the urban/rural poverty

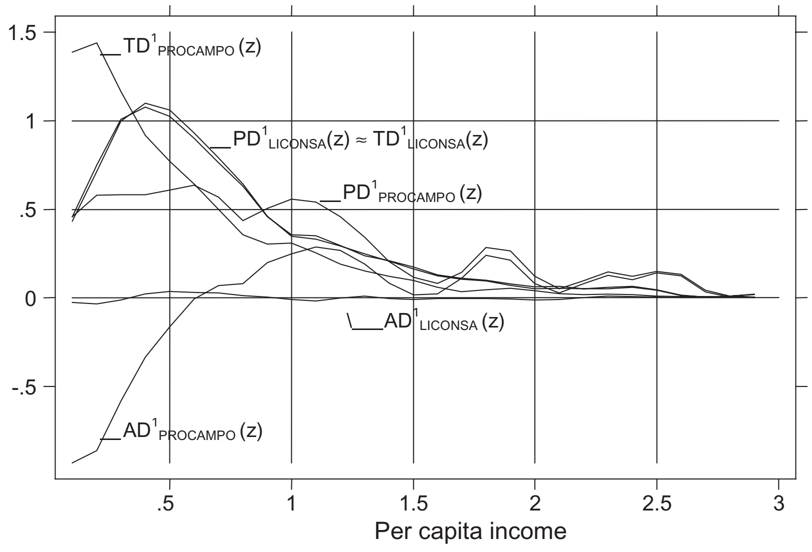

Fig. 1. Procampo vs. Liconsa, poverty dominance, s=1. Source: Authors' estimation using 1997 ENCASEH.

line used in a recent World Bank poverty assessment for Mexico.[13] With these poverty lines, which are on the high side, 68.7% of the population is poor (those with *per capita* income below z=1).

The precise values of the $PD^1(z)$ and $TD^1(z)$ curves for z=0.5, z=1, and z=2 and their standard errors are given in Table 1. The standard errors can be derived from the formulas provided in Duclos et al. (2002) and can be estimated using the DAD software (Duclos et al., 2001). The values of the $AD^1(z)$ curves for the various thresholds are not given in the table, but they can be readily obtained as the differences between the $PD^1(z)$ and $TD^1(z)$ curves. The two $PD^1(z)$ curves cross at $\hat{z}_P^1$=0.889, with a standard error of 0.047. Hence for any choice of poverty line z below approximately z=0.812, if there were no differences in relative economic efficiency between the two programs (γ=1), a policy maker could be confident (with a statistical confidence level of 95%) that increasing funding for a proportional increase in the generosity of Liconsa and reducing funding for a proportional decrease in the generosity of PROCAMPO would reduce poverty for all poverty indices belonging to $\Pi^1(z)$.

Recall that by (19) the $PD_k^s(z)$ curve gives directly the impact of a marginal proportional increase in program k's expenditures on the $FGT^{s-1}(z)$ poverty index-per peso of additional per capita expenditures (here expressed in units of the poverty line). $PD^1(z)$ thus provides immediately the impact of a program extension on the poverty headcount. Note that the point estimates of the two $PD^1(z$=1) suggest that it would better to downsize Liconsa and enhance PROCAMPO to reduce the poverty headcount. This is clearly in conflict with the recommendation of the previous paragraph: it shows how the choice of poverty lines can matter for poverty and policy analysis. Note also, however, that

[13] See World Bank (1999).

Table 1
Comparison of Procampo and Liconsa for s=1, Mexico 1997

	Value of PD and TD curves at various poverty lines for s=1		
	Liconsa (1)	Procampo (2)	Difference (1)−(2)
Program dominance (PD) curves			
z=0.5	1.060 (0.059)	0.608 (0.098)	0.452 (0.114)
z=1	0.347 (0.035)	0.556 (0.134)	−0.209 (0.134)
z=2	0.050 (0.012)	0.121 (0.046)	−0.070 (0.048)
Targeting dominance (TD) curves			
z=0.5	1.024 (0.060)	0.771 (0.064)	0.252 (0.086)
z=1	0.357 (0.038)	0.308 (0.045)	0.049 (0.059)
z=2	0.062 (0.016)	0.040 (0.019)	0.022 (0.025)

Source: Authors' estimation using 1997 ENCASEH. Sample size is 9911 observations. Incomes are normalized by regional poverty lines.

the differences between the $PD^1(z)$ curves are not statistically significant beyond their crossing point at around $\hat{z}_P^1$=0.89.

While a $PD^1(z)$ curve gives the density of *program benefits* enjoyed by individuals with income z, the $TD^1(z)$ curves give the density of *program beneficiaries* at that same income. This useful descriptive information is again shown on Fig. 1. The area underneath each of the density curves necessarily gives 1. The two $TD^1(z)$ curves cross at $\hat{z}_T^1$=0.349, with a standard error of 0.029. For a range of poverty lines up to about z=0.3 a policy maker could be 95% certain that increasing funding for a lump-sum bonification of PROCAMPO, and reducing funding for a lump-sum decrease of Liconsa benefits, would be first-order poverty dominant and improve the performance of the two programs taken jointly. For poverty lines beyond about 0.4, the opposite conclusion would hold.

The difference between the $PD^1(z)$ and $TD^1(z)$ curves is shown on the figure by the $AD^1(z)$ curves. This is the difference between the density of program benefits and of program beneficiaries. Because there are very few differences in Liconsa per capita benefits by income level among Liconsa recipients (even though there are differences in total benefits, in proportion to the number of children below the age of 12 found in the household), the $PD^1(z)$ and $TD^1(z)$ curves are nearly identical, so that the $AD^1(z)$ curve takes a value close to zero throughout. For PROCAMPO however, and for low poverty lines, values of the $AD^1(z)$ curve are large and negative, suggesting a loss in benefits for the very poor in comparison to the share of benefits that they would have had if there had been no differences in benefits among program participants.

PROCAMPO thus gives a clear example of the role of the allocation mechanism among program participants with respect to the overall poverty impact of a program. While many PROCAMPO beneficiaries are poor farmers with small plots of land, some of the beneficiaries are fairly rich farmers with large landholdings, and thereby recipients of large PROCAMPO transfers since the transfers are proportional to the amount of land cultivated. Changing the allocation mechanism for PROCAMPO (that is, *reducing* its spread) would certainly improve the program's impact on extreme poverty in Mexico.

3.3. Second-order poverty dominance

Some of the findings obtained for first-order poverty dominance become stronger when we consider second-order poverty dominance, that is, when we focus solely on "distribution-sensitive" poverty indices. These findings are shown on Fig. 2 and Table 2. Recall that the $PD^2(z)$ and $TD^2(z)$ curves represent, respectively, the cumulative proportions (or cumulative densities) of program benefits and of program beneficiaries found in households with *per capita* income below a certain level. For example, the population below z=0.5 is estimated to account for 41.9% of Liconsa beneficiaries and 41.1% of Liconsa transfers. The same population includes 63.6% of the PROCAMPO beneficiaries and 28.1% of the PROCAMPO transfers.

We now observe that the targeting performance of PROCAMPO is unambiguously better than that of Liconsa over a large range of poverty lines, even though enhancing Liconsa and downsizing PROCAMPO is now second-order poverty dominant over a similarly large range of poverty lines–extending to well above z=1–again, under the assumption that marginal economic efficiency is similar for the two programs. Note here a striking conflict between the policy conclusions drawn under alternative choices of poverty lines and poverty indices. Fig. 1 suggested that it would be better proportionately to downsize Liconsa and expand PROCAMPO if the aim was to reduce the headcount index at z=1. Fig. 2 reveals instead that it is better to invest additional resources in Liconsa at the expense of PROCAMPO for all distributive-sensitive poverty indices (this excludes the headcount, which does not obey the Pigou-Dalton transfer principle) and for any reasonable choice of poverty line.

The two $PD^2(z)$ curves still cross, but the crossing point is not shown on the graph since it takes place at $\hat{z}_P^2$=3.931, with a standard error of 0.020. That the ranking of these two

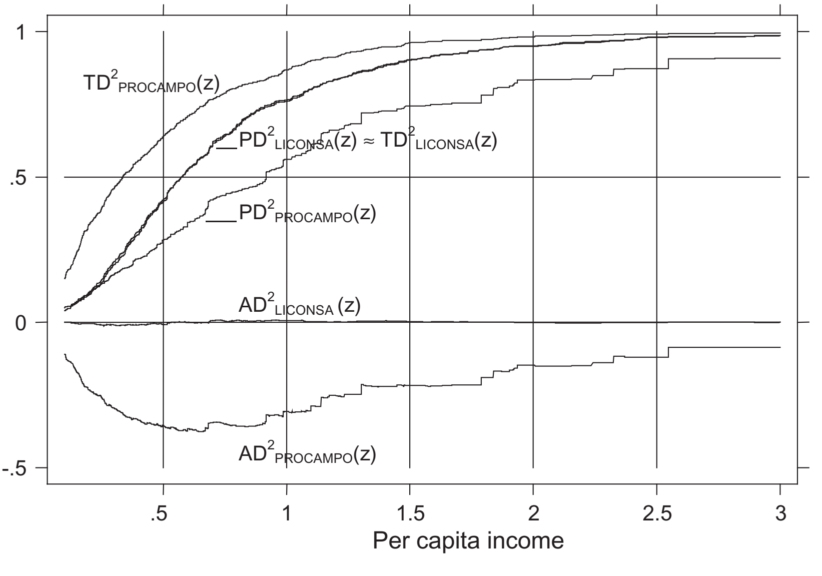

Fig. 2. Procampo vs. Liconsa, poverty dominance, s=2. Source: Authors' estimation using 1997 ENCASEH.

Table 2
Comparison of Procampo and Liconsa for s=2, Mexico 1997

	Value of PD and TD curves at various poverty lines for s=2		
	Liconsa (1)	Procampo (2)	Difference (1)–(2)
Poverty dominance (PD) curves			
z=0.5	0.411 (0.018)	0.281 (0.037)	0.130 (0.041)
z=1	0.764 (0.016)	0.560 (0.063)	0.203 (0.065)
z=2	0.949 (0.008)	0.834 (0.067)	0.115 (0.067)
Targeting dominance (TD) curves			
z=0.5	0.419 (0.020)	0.636 (0.023)	−0.217 (0.030)
z=1	0.759 (0.017)	0.868 (0.015)	−0.109 (0.023)
z=2	0.950 (0.008)	0.982 (0.006)	−0.031 (0.010)

Source: Authors' estimation using 1997 ENCASEH. Sample size is 9911 observations. Incomes are normalized by regional poverty lines.

$PD^2(z)$ curves is valid over a larger range of poverty lines than for $PD^1(z)$ follows from Lemma 1 in Davidson and Duclos (2000). Since the differences between the $PD^2(z)$ curves are statistically significant for a large range of z values, a proportional policy reform involving the two programs would lead to a statistically significant reduction in the average poverty gap, for a wide selection of alternative poverty lines.

Importantly, therefore, while PROCAMPO is better targeted than Liconsa, Liconsa is the better program overall for proportional reforms of the program, viz, when the allocation of benefits among program participants is also taken into account. Clearly, judging from the $AD^2(z)$ curves of Fig. 2, an allocative reform that decreased the spread of PROCAMPO benefits from the mean would be much more favorable to poverty alleviation than a similar allocative reform for Liconsa.

3.4. The role of economic efficiency

We have assumed so far that the economic efficiency of the two programs was the same—that is, that γ=1. While both programs are funded through general tax revenues (so that there is no difference in the marginal cost of public funds), the programs may have different behavioral and incentive effects. Research by Cord and Wodon (2001) and Sadoulet et al. (1999) suggests that PROCAMPO may have multiplier effects, so that one peso in transfers generates additional nominal revenues for program participants. Various hypotheses have been advanced to explain this multiplier effect. Thanks to cash availability and the lifting of liquidity constraints, or thanks to a reduction in the risk faced by program beneficiaries, PROCAMPO may increase household investment and/or enable households to choose riskier investments with higher expected rates of return. PROCAMPO's transfers may also be large and concentrated enough to stimulate the local economy, raising the demand for local goods and services, thereby creating new income and tax generating activities. Whatever the reason for PROCAMPO's multiplier effect, if such a multiplier effect exists for PROCAMPO but not for Liconsa, then the ranking of the two programs may be altered.

Return to Proposition 1. Assume, for the sake of the argument, that (because of the additional tax revenues it generates) PROCAMPO is half as costly to finance as Liconsa. For checking poverty dominance, this is equivalent to multiplying PROCAMPO's $\mathrm{PD}^s(z)$ curves by two (for all orders of poverty dominance). It can be shown in that case that the $\mathrm{PD}^s(z)$ curves for PROCAMPO would always be above those of Liconsa, whatever the value of s and of the income cut-off z. Hence, directing more resources towards PROCAMPO at the expense of Liconsa would clearly be deemed poverty reducing for any reasonable choice of poverty measures and poverty lines. Although this paper's objective is obviously not to settle definitely this issue of the relative economic and poverty efficiency of these two Mexican programs, the methodology proposed in it indicates clearly why and how such issues can matter for the assessment and the design of public policy.

4. Conclusion

This paper shows how simple graphical tools can be used to assess the poverty impact of different programs and of marginal reforms to them. Program dominance curves are decomposed into the sum of a targeting dominance curve, which only takes into account who benefits from the program, and an allocation dominance curve, which reflects potentially large differences in allocations between program participants. Apart from generating substantial and useful descriptive evidence on the incidence of transfer programs, the use of these curves enables analysts to assess the poverty impact of program reforms without having to make strong assumptions on the exact value of poverty lines, on the nature of the poverty measures to be used, or on the reforms' disaggregated behavioral impacts. They also give valuable information to detect the differential effect of targeting and allocation rules and of economic efficiency effects on the overall performance of various programs and program reforms.

Acknowledgement

This paper was funded through the World Bank Research Support Budget under the research project "The impact of changes in prices, taxes, subsidies and stipends on poverty when households differ in needs" and has also benefitted from the support of SSHRC, FQRSC, the MIMAP program of IDRC and the Bureau de la recherche of Université de Sherbrooke. We thank two anonymous referees for very useful comments.

Appendix A. Proof of propositions

A.1. Proof of Proposition 1

Suppose two income distributions A (before a program reform) and B (after a program reform). Duclos and Makdissi (2004) show that a necessary and sufficient condition for poverty to decrease when moving from A to B, for all $P(z)\in\Pi^{s}(z)$, for all $z\in[0,z^{+}]$, and for any given $s\in\{1,2,3,\ldots\}$, is given by

$$D_A^s(y)\geq D_B^s(y)\ \forall y\leq z^{+}, \tag{32}$$

where

$$D_A^s(y)=\int_0^y (y-x)^{s-1}\mathrm{d}F_A(x). \tag{33}$$

Note that the continuity assumption $p^{(t)}(z,z)=0$ for all $t\in\{1,2,\ldots,s-2\}$ in (11) is important for ordering distributions at dominance orders 3 and higher. In the context of a marginal program reform, this necessary and sufficient condition naturally becomes

$$\mathrm{d}D^s(y)\leq 0\ \forall y\leq z^{+}. \tag{34}$$

We have that

$$\mathrm{d}D^s(y)=\frac{\partial D^s(y)}{\partial t_k}\Delta t_k+\frac{\partial D^s(y)}{\partial t_l}\Delta t_l. \tag{35}$$

Using revenue neutrality, (16) and (17), (35) may be rewritten as

$$\mathrm{d}D^s(y)=\left[\frac{\partial D^s(y)}{\partial t_k}-\gamma\frac{T_k}{T_l}\frac{\partial D^s(y)}{\partial t_l}\right]\Delta t_k.$$

From Eq. (19), we obtain

$$\mathrm{d}D^s(y)=z^{s-1}T_k\left[-PD_k^s(y)+\gamma PD_l^s(y)\right]\Delta t_k. \tag{36}$$

Using (36), for $\Delta t_k>0$ condition (34) is then equivalent to

$$PD_k^s(y)-\gamma PD_l^s(y)\geq 0,\quad \forall y\in[0,z^{+}].$$

A.2. Proofs of Propositions 2, 3 and 4

Considering the definitions (22) and (25) and the proof of proposition 1, the Proofs of Propositions 2, 3 and 4 follow readily.

References

Ahmad, E., Stern, N.H., 1984. The theory of reform and Indian indirect taxes. Journal of Public Economics 25, 259–298.

Ahmad, E., Stern, N.H., 1991. The theory and practice of tax reform in developing countries. Cambridge University Press, Cambridge.

Atkinson, A.B., 1987. On the measurement of poverty. Econometrica 55, 759–764.

Baker, J.L., Grosch, M.E., 1994. Poverty reduction through geographic targeting: how well does it work. World Development 22, 983–995.

Besley, T., Kanbur, R., 1988. Food subsidies and poverty alleviation. Economic Journal 98, 701–719.

Chakravarty, S.R., 1983. Ethically flexible measures of poverty. Canadian Journal of Economics 16, 74–85.

Coady, D., Skoufias, E., 2001. On the targeting and redistributive efficiencies of alternative transfer instruments, mimeo, International Food Policy Research Institute, Washington DC.

Cord, C., Wodon, Q., 2001. Do Mexico's agricultural programs alleviate poverty? Evidence from the ejido sector. Cuadernos de Economia 114, 239–256.

Cornia, G.A., Stewart, F., 1995. Two errors of targeting. In: Van de Walle, D., Nead, K. (Eds.), Public Spending and the Poor: Theory and Evidence. John Hopkins University Press, Baltimore.

Datt, G., Ravallion, M., 1992. Growth and redistribution components of changes in poverty measures—a decomposition with applications to Brazil and India in the 80's. Journal of Development Economics 38, 275–296.

Davidson, R., Duclos, J.Y., 2000. Statistical inference for stochastic dominance and the for the measurement of poverty and inequality. Econometrica 68, 1435–1465.

Duclos, J.Y., Makdissi, P., 2004. Restricted and unrestricted dominance for welfare, inequality and poverty orderings. Journal of Public Economic Theory 6, 145–164.

Duclos, J.Y., Araar, A., Fortin, C., 2001. DAD: a software for distributive analysis/analyse distributive. MIMAP program, International Development Research Centre, Government of Canada and CRÉFA, Université Laval (freely available at http://www.mimap.ecn.ulaval.ca).

Duclos, J.Y., Makdissi, P., Wodon, Q., 2002. Socially-Efficient Tax Reforms, Cahier De Recherche 02-01. Département d'économique, Université de Sherbrooke.

Feldstein, M.S., 1975. The income tax and charitable contributions: Part I. Aggregate and distributional effects. National Tax Journal 28, 81–100.

Foster, J., Shorrocks, A.F., 1988a. Poverty orderings. Econometrica 56, 173–177.

Foster, J.E., Shorrocks, A.F., 1988b. Poverty orderings and welfare dominance. Social Choice and Welfare 5, 179–198.

Foster, J.E., Shorrocks, A.F., 1988c. Inequality and poverty orderings. European Economic Review 32, 654–662.

Foster, J., Greer, J., Thorbecke, E., 1984. A class of decomposable poverty measures. Econometrica 52, 761–776.

Grosch, M.E., 1995. Towards quantifying the trade-off: administrative costs and incidence in targeted programs in Latin America. In: Van de Walle, D., Nead, K. (Eds.), Public Spending and the Poor: Theory and Evidence. John Hopkins University Press, Baltimore.

Jenkins, S.P., Lambert, P.J., 1997. Three 'I's of poverty curves, with an analysis of UK poverty trends. Oxford Economic Papers 49, 317–327.

Kakwani, N.C., 1977. Measurement of tax progressivity: an international comparison. Economic Journal, 71–80.

King, M.A., 1983. Welfare analysis of tax reforms using household data. Journal of Public Economics 21, 183–214.

Lanjouw, P., Ravallion, M., 1999. Benefit incidence, public spending reforms, and the timing of program capture. World Bank Economic Review 13, 257–273.

Makdissi, P., Wodon, Q., 2002. Consumption dominance curves: testing for the impact of indirect tax reforms on poverty. Economics Letters 75, 227–235.

Mayshar, J., Yitzhaki, S., 1995. Dalton improving tax reform. American Economic Review 85, 793–807.

McKenzie, L., 1956. Demand without a utility index. Review of Economic Studies 24, 185–189.

Pfähler, W., 1987. Redistributive effects of tax progressivity: evaluating a general class of aggregate measures. Public Finance/Finances Publiques 42, 1–31.

Rao, V.M., 1969. Two decompositions of concentration ratio. Journal of the Royal Statistical Society, Series A 132, 418–425.

Ravallion, M., 1994. Poverty comparisons. Harwood Academic Publishers, Chur.

Ravallion, M., Datt, G., 1995. Is targeting through a work requirement efficient? Some evidence for rural India. In: Van de Walle, D., Nead, K. (Eds.), Public Spending and the Poor: Theory and Evidence. John Hopkins University Press, Baltimore.

Ravallion, M., Huppi, M., 1991. Measuring changes in poverty: a methodological case study of Indonesia during an adjustment period. World Bank Economic Review 5, 57–84.

Sadoulet, E., de Janvry A., Davis, B., 1999. Cash Transfer Programs with Income Multipliers: PROCAMPO in Mexico, Mimeo, University of California at Berkeley.

Samuelson, P.A., 1974. Complementarity—an essay on the 40th anniversary of the Hicks-Allen Revolution in demand theory. Journal of Economic Literature 12, 1255–1289.

Shapley, L.S., 1954. A value for n-person games. In: Kuhn, Harold W., Tucker, A. William (Eds.), Contributions to the Theory of Games II, Annals of Mathematical Studies, vol. 28. Princeton University Press, pp. 307–317.

Shorrocks, A.F., 1995. Revisiting the Sen poverty index. Econometrica 63, 1225–1230.

Shorrocks, A.F., 1999. Decomposition Procedures for Distributional Analysis: A Unified Framework Based on the Shapley Value, Mimeo.

Skoufias, E., 2001. PROGRESA and its Impact on the Human Capital and Welfare of Households in Rural Mexico: A Synthesis of the Results of an Evaluation by IFPRI. International Food Policy Research Institute, Washington, DC.

Slemrod, J., Yitzhaki, S., 1996. The cost of taxation and the marginal efficiency cost of fund. International Monetary Fund Staff Papers 43, 172–198.

Thon, D., 1979. On measuring poverty. Review of Income and Wealth 25, 429–439.

Varian, H., 1980. Notes on Cost-Benefit Analysis, Mimeo.

Wodon, Q., 1997. Targeting the poor using ROC curves. World Development 25, 2083–2092.

Wodon, Q., Yitzhaki, S., 2002. Evaluating the impact of government programs on social welfare: the role of targeting and the allocation rules among program beneficiaries. Public Finance Review 30, 102–123.

World Bank, 1999. Government Programs and Poverty in Mexico, Report No. 19214-MX, Washington, DC.

Yitzhaki, S., Slemrod, J., 1991. Welfare dominance: an application to commodity taxation. American Economic Review 81, 480–496.

Zheng, B., 1999. On the power of poverty orderings. Social Choice and Welfare 3, 349–371.

Zheng, B., 2000a. Poverty orderings. Journal of Economic Surveys 14, 427–466.

Zheng, B., 2000b. Minimum distribution-sensitivity, poverty aversion, and poverty orderings. Journal of Economic Theory 95, 116–137.