Why May Government Transfers to the Poor Have Modest Effects on Reducing Rural Inequality?*

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Abstract

High levels of inequality are a persistent feature of many rural areas in the developing world. Rural inequality is correlated with major impediments of rural development, such as crime, elite-capture, and lack of collective action. Government transfer programs, such as conditional cash transfer (CCT), unemployment insurance, old-age pension or similar programs that target the lower tail of a village's cumulative welfare distribution function have become a very popular public policy to tackle poverty and inequality in rural areas. In India, for example, there is the Government's flagship program, the National Rural Employment Guarantee Act (NREGA) which provides cash to the rural poor. Furthermore India has launched the Janani Suraksha Yojana Program (JSY), a CCT to incentivise women to give birth in a health facility. Moreover, in March 2008 the Indian Government introduced the 'Dhanalakshmi' CCT, implemented on an experimental basis in several parts of the country which provides cash transfers for childrens' birth registration, immunization, enrollment and retention in school. While the poverty impacts of those programs are well documented in the literature less attention has been given to the redistributive capacity of such policies at the village level. Among the main reasons for the neglect is a common belief that monetary transfers to the lower tail of the village welfare distribution (i.e. 'the poor'), while excluding the upper tail (i.e. 'the rich') from the program, must lead to a reduction in inequality. In this paper we show that the impact of such programs on reducing rural inequality may be lower than previously thought. This is because program-eligible lower and program-ineligible upper tail do not behave in isolation from each other. They are linked via interactions in credit & insurance, as well as factor & commodity markets. If, consequently, a government transfer triggers the lower tail to shift then the upper tail follows, leading to modest reductions in local inequality.

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1 Introduction

High levels of inequality are a persistent feature of many rural areas, home of almost 80 percent of the world's population. Using data from several pre-industrialized countries, Elbers et al. (2004) show that significant levels of inequality still exist even in the poorest communities in rural areas. The literature emphasizes that a large proportion of rural inequality may be explained by low levels of asset endowments (Zimmerman and Carter, 2003), relatively high transaction costs such registration fees, titling and information (Renkow et al., 2004), and lack of access to credit markets for the lower tail of the rural welfare distribution ((De Janvry and Sadoulet, 2000); Dercon (1998)). The local level of inequality is correlated with major impediments of rural development, such as crime (Kelly, 2000), elite-capture (Bardhan and Mookherjee (2002); (Araujo et al., 2008); Mansuri and Rao (2004)), targeting performance of anti-poverty programs (Galasso and Ravallion, 2005), and lack of collective action (Dayton-Johnson and Bardhan (2002);Chwe (1999)).[1]

Government transfer programs, such as conditional cash transfer, unemployment insurance, old-age pension or similar programs targeting the lower tail of the rural welfare cumulative distribution function are increasingly being implemented by governments to reduce poverty and inequality in rural areas. In India, for example, there is the Government's flagship program, the National Rural Employment Guarantee Act (NREGA) which provides cash to the rural poor. Furthermore India has launched the Janani Suraksha Yojana Program (JSY), a conditional cash transfer scheme, to incentivise women to give birth in a health facility. Moreover, in March 2008, the Indian Government introduced the 'Dhanalakshmi' Conditional Cash Transfer Program, implemented on an experimental basis in 11 educationally backward blocks across Andhra Pradesh, Uttar Pradesh, Bihar, Orissa, Jharkhand, Chhattisgarh and Punjab. 'Dhanalakshmi' provides cash transfers to the family of a female child on their fulfilling specific conditions: birth and registration of the child, immunization, enrollment and retention in school.

The effects of such programs on poverty have received a considerable amount of attention in the literature.[2] Through increasing household income, these programs are associated with a significant rise in household

[1] See Mansuri and Rao (2004) for an overview of both theoretical and empirical literature.
[2] see Lindert et al. (2006) and Fizbein and Schady (2009) for a comprehensive overview.

consumption at the lower tail of the rural welfare distribution. Maybe it is this kind of evidence that has prevented more research on the redistributive capacities of such policies at the village level. The latter may seem to be a trivial exercise since the program-induced consumption increase at the lower tail of a rural village's welfare distribution should, ceteris paribus, lead to a reduction in inequality.

In this paper we contribute to the literature on the distributional impacts of public policies (see Bourguignon and Spadaro (2006), Cunha et al. (2006), Bitler et al. (2006) for some recent examples) by showing that the impact of such government transfer programs on reducing rural inequality may be lower than previously thought. This is because program-eligible lower and program-ineligible upper tail of the villages cumulative welfare distribution function do not behave in isolation from each other. They are linked via interactions in credit & insurance, as well as factor & commodity markets. If, consequently, a government transfer triggers the lower tail to shift then the upper tail follows, leading to modest reductions in local inequality.

The remainder of this paper is structured as follows. Section 2 describes the setup for empirical analysis. We exploit the unique implementation design of a Mexican government program to tease out the causal effect of the program on village inequality. The latter turns out to be lower than expected. In an attempt to shed light on the reason for this at a first glance surprising result section 3 then explores the existence of linkages along the village welfare distribution. We show that interactions in credit & insurance, as well as factor & commodity markets create a situation whereby monetary government transfers granted to the lower tail of the village welfare distribution do lead to welfare improvements at the program-ineligible upper tail. Finally, section 4 concludes.

2 Distributional Effects of Government Transfers at the Village Level

2.1 The Setup for Empirical Analysis

We define inequality as a functional ν of the distribution of some outcome Y, $\nu : F_Y \rightarrow \Re$. Some of the most frequently used inequality measures are[3]:

[3] see Cowell (2000) for a recent survey of methods of inequality measurement

1. Gini Coefficient (GC):

$$\nu^{GG}(F_Y) = 1 - 2\frac{\int_0^1 \int_{-\infty}^{\nu^{Q_\tau}(F_Y)} y \cdot dF_Y(y)d\tau}{\int y \cdot dF_Y(y)} \tag{1}$$

2. Coefficient of Variation (CV):

$$\nu^{CV}(F_Y) = \frac{(\int (y - \int z \cdot dF_Y(z))^2 \cdot dF_Y(y))^{1/2}}{\int y \cdot dF_Y(y)} \tag{2}$$

Let $F_{Y(1)}$ be the cdf of outcome y in some village j where a government transfer program is available to households belonging to the lower tail of the village's welfare cumulative distribution function, and $F_Y(0)$ denote the cdf of the same village had the program not been present. The average effect of the program on village inequality, henceforth the inequality treatment effect (AIE) is then given by the expression

$$AIE = E[\nu_j(F_{Y(1)})|P_j = 1] - E[\nu_j(F_{Y(0)})|P_j = 1]. \tag{3}$$

The identification problem arises from the fact that we can only observe the level of inequality of some village j in either the presence or the absence of the program, but never in the two states at the same time. If assignment of villages to the program is random then the expected level of inequality in program villages had the program not been assigned to the village, equals the expected level of inequality in villages that have not been assigned to the program. Formally,

$$E[\nu_j(F_{Y(0)})|P_j = 1] = E[\nu_j(F_{Y(0)})|P_j = 0]. \tag{4}$$

The expression on the right hand side, thus, provides a valid counterfactual for the expected level of inequality in program villages had the program not been implemented. Substituting yields our estimator for the average village inequality treatment effect

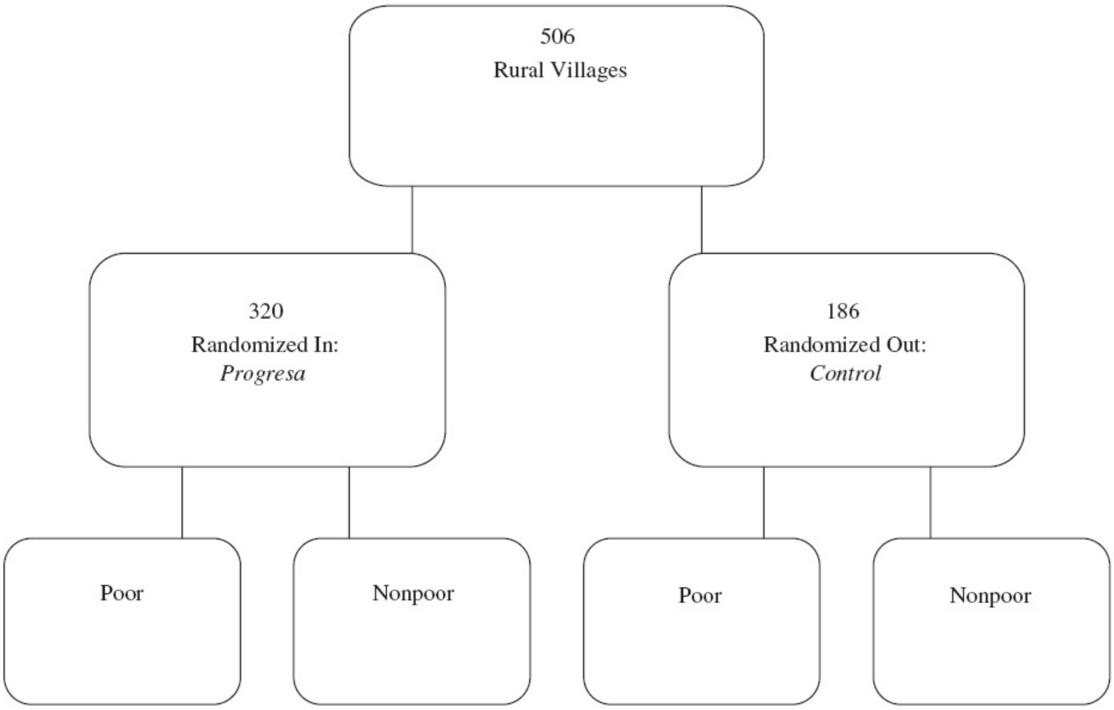
$$\widehat{AIE_1} = E[\nu_j(F_{Y(1)})|P_j = 1] - E[\nu_j(F_{Y(0)})|P_j = 0] \tag{5}$$

which is obtained by the following OLS regression

$$\nu_j = \alpha_0 + \theta_1 P_j + \beta \mathbf{Z_j} + u_j \tag{6}$$

where θ_1 is an estimator for the AIE, $\mathbf{Z_j}$ is a vector of village controls in order to increase the precision of the estimate, and u_j denotes a random error.

Figure 1: The Experimental Design



2.2 The Data

In 1997, the Mexican government started the so called *Progresa* program with the aim of reducing rural poverty and inequality (Schultz, 2004). The program provides monetary grants to the lower tail of the village welfare distribution, i.e. the poorest households of a village. In order to identify the latter, the Mexican government used a multidimensional poverty index.[4] *Progresa* monetary grants are of substantial size, amounting to about 20 percent of average household income in rural Mexico.

For the purpose of impact evaluation and feasibility of program implementation, the program was initially not implemented simultaneously in all villages. In 1997, the Mexican government determined all eligible households. Then, a set of villages where the program ought to be implemented first was chosen randomly. Households classified as 'poor' in these villages would receive the first *Progresa* transfer payment in early 1998. The remaining villages would only be incorporated into the program two years later. Households classified as 'poor' in these villages would receive the first *Progresa* transfer only in early 2000. The latter, therefore, serve as a control group for the years 1998 and 1999. In some

[4]see Skoufias et al. (2001) for a description of the method.

320 villages where the program would be implemented first (henceforth referred to as 'treatment villages') and in another 186 villages where the program would start two years later (henceforth referred to as 'control villages') the Mexican government conducted a comprehensive baseline, and a three follow-up surveys between and 1998 and 1999. These surveys are village censuses whereby data on all residents of these 506 villages was collected. We thus have a panel of the entire village welfare cumulative distribution function, consisting of program-eligible households at the lower tail and program-ineligible households at the upper tail, in each of the 320 treatment and 186 control villages. Figure 1 shows the structure of the experimental design. The experimental design of the program in combination with the census nature of these surveys allows us to calculate and compare the level of inequality in treatment versus control villages. Under random assignment of villages to the program, equation 6 identifies the impact of the program on village inequality.[5]

Prior to the start of the program these 506 villages have characteristics that would describe many village economies across the globe. The average village size is 45 households, 95 percent of which report agriculture to be their main source of livelihood. One year after the start of the program, on average 60 percent of residents in treatment villages receive the government transfer. Table 1 shows descriptive statistics of households classified eligible (i.e. 'poor') and households classified ineligible (i.e. 'non-poor') by the government.[6] The table suggests that the program was effective in targeting the lower tail of the village welfare distribution, i.e. the poorest households of a village. Program-eligible households have, on average lower food consumption, income and education levels, as well as lower land and livestock holdings, compared to program-ineligible households. These differences are all statistically significant.

Inequality is substantial these 506 villages. For example, the average village gini coefficient for household income (plus value of consumed own agricultural production) is 0.44.

[5] See for example Behrman and Todd (1999) who, for a vector of village characteristics, cannot reject the null of zero mean difference between treatment and control villages at baseline .

[6] We present descriptive statistics of the control group, one year after the start of the program. Ideally, we would present characteristics of all sample households in both treatment and control villages prior to the start of the program. Unfortunately, key variables such as food consumption and income plus value of consumed own agricultural production are not available in the baseline survey.

Table 1: Characteristics of the Counterfactual Sample

	Eligible Households	Ineligible Households
	Mean [Std.Dev.]	Mean [Std.Dev.]
Household and Community Characteristics		
Gini Index for agricultural land ownership	0.71	
	[120.7]	[124.9]
Pre-program household poverty score	701.6	882.5
	[120.7]	[124.9]
Monthly Food consumption (per capita, peso value)	182.5	198.4
	[163.6]	[153.2]
Monthly Food expenditure (per capita, peso value)	137.3	169.6
	[130.1]	[145.4]
Monthly non-purchased food consumption (per capita, peso value)	38.85	27.86
	[591.9]	[48.1]
Monthly household disposable income (in peso)	662.1	795.3
	[362.6]	[2129.8]
Cultivated area (in hectare)	0.46	0.75
	[2.77]	[2.31]
Hourly wage rate	5.27	6.97
	[36.14]	[25.12]
Livestock holding index	-0.21	0.06
	[2.41]	[3.63]
Household size	5.44	4.82
	[2.60]	[2.53]
Indigenous household head	0.36	0.17
	[0.48]	[0.37]
Education of head		
no	32.55	26.35
primary	62.03	64.52
secondary	4.92	6.95
tertiary	0.51	2.19
N	6857	1949

Notes: standard deviations are reported in parenthesis. Livestock index calculated using principal component analysis

Table 2: Average inequality treatment effect for food consumption, two years after the start of the program

	(Household monthly food consumption (p.a.e)		Household monthly income (plus VCOAP)	
	Observed AIE	Simulated AIE	Observed AIE	Simulated AIE
	θ_1	θ_2	θ_1	θ_2
Gini Coefficient	-.006	-.015***	-.004	-.014*
	[.004]	[.004]	[.007]	[.008]
Coefficient of Variation	-.007	-.029**	-.038*	-.046*
	[.010]	[.011]	[.022]	[.024]
	$n = 506$	$n = 372$	$n = 506$	$n = 372$

Notes: *Significant at 10%; **significant at 5%; ***significant at 1%. Standard errors are reported in parenthesis. VCOAP stands for value of consumed own agricultural production, and p.a.e stands for 'per adult equivalent'.

2.3 Results: Average Inequality Treatment Effects

The first column in table 2 shows the village inequality treatments effect using food consumption as a proxy for household welfare. We cannot reject the null of zero reduction in food consumption inequality in treatment villages. As a consistency check we also consider income (plus the value of consumed own agricultural production) as outcome variable. While we observe a small reduction of .038 in the coefficient of variation, we cannot reject the null of no change in a village's gini coefficient.

Why may a program that provides monetary grants to the lower tail of the village welfare distribution have rather modest effects on reducing village inequality? Maybe the program had no significant effect on outcomes of transfer recipients. We can rule out this possibility by referring to Hoddinott and Skoufias (2004) and Angelucci and De Giorgi (2009) who found sizeable effects of the program on transfer recipient's food consumption and income levels. Consequently, in order to explain the modest program effect on village inequality, it must be that welfare gains at the lower tail of village welfare distribution do 'spill-over' to the program-ineligible upper tail.

In order to see what reductions in inequality we would expect in the absence of such 'spillover' we conduct a static microsimulation of the *Progresa* monetary transfer on program-eligible households residing in control villages. The microsimulation procedure is as follows:[7] In a first step, we estimate the level of inequality in each control village (186 villages). We call the vector of obtained measures group zero ($G = 0$). In a

[7] We refer the reader to the appendix for more details on the microsimulation.

second step, we add the *Progresa* monetary transfer to household income of each program-eligible household in the control group, then determine the consequent change in each eligible household's food consumption and income plus value of consumed own agricultural production, in order to finally recalculate inequality measures in each control village. We call the vector of obtained measures group one ($G = 1$). In a third step, we calculate the simulated average inequality treatment effect on the control group as

$$\begin{aligned}\widehat{AIE}_2 &= E[\nu_j|G=1] - E[\nu_j|G=0] \\ &= E[\nu_j(F_{Y(0)+\tau})|P_j=0] - E[\nu_j(F_{Y(0)})|P_j=0] \qquad (7)\end{aligned}$$

where $E[\nu_j(F_{Y(0)})|P_j = 0]$ is the expected level of inequality in control villages without the program, and $E[\nu_j(F_{Y(0)+\tau})|P_j = 0]$ is the expected level of inequality in the same villages after adding the monetary transfer to eligible households residing in those villages. The simulated average inequality effect is obtained by the following OLS regression on control villages ($P_j = 0$):

$$\nu_j = \alpha_0 + \theta_2 G_j + \beta \mathbf{Z_j} + u_j \qquad \forall\ j\ \in\ P_j = 0 \qquad (8)$$

where θ_2 is an estimator of the AIE **in the absence of** 'spillover' from the program-eligible lower to the program-ineligible upper tail of a village's welfare distribution. $\mathbf{Z_j}$ is a vector of village controls in order to increase the precision of the estimate, and u_j denotes a random error.

The second and fourth column in table 2 show the results of the microsimulation. The simulated average inequality treatment effect for food consumption is higher than the observed inequality treatment effect. For the gini coefficient, for example, we estimate a reduction of .015, while the observed reduction is .006. The simulated reduction in the coefficient of variation is .029. while the observed reduction is .011. A similar pattern holds when considering income (plus the value of consumed own agricultural production) as outcome variable. The simulated reduction in inequality as measured by the gini coefficient is .014, compared to an observed reduction of .004. The simulated reduction in the coefficient of variation is .046, compared to an observed reduction of .038.

Figure 2 visualizes the effect of the program on the entire food consumption cumulative distribution function (cdf). Plotted are the cdf of household food consumption (monthly, per capita) in treatment (320 villages), control (186 villages), and simulated villages (186 villages), respectively.

The upper graph shows the lower tail of the cdf. The monetary transfer induces the cdf to shift to the right, i.e. program participants consume more food. The simulated cdf predicts almost exactly the observed cdf. As one moves upwards the distribution, however, the simulated cdf converges with the 'no-program' cdf. This is because the number of eligible households converges towards zero as one moves upward in the distribution. However, even through the number of program-eligible (i.e. 'poor') households converges towards zero as one moves upward the distribution, the observed effect on food consumption stays roughly constant, suggesting that program-ineligible households (i.e. the 'non-poor') do also increase food consumption, even through they do not receive the government monetary transfer. Indeed, when comparing the level of monthly per capita household food consumption of program-ineligble households in treatment versus control villages we find the former to be 20 peso higher than the latter.[8] The fact that both lower and upper tail of the distribution shift to the right then explains why we observe no reduction in inequality in program villages.[9]

Why does the upper tail follow the lower tail, although the latter receives the bulk of the government transfer? In the following we'll explore linkages along the rural welfare distribution. Program-eligible lower tail and program-ineligible upper tail do not behave in isolation from each other. They are linked via interactions in credit & insurance, as well as factor & commodity markets. If, consequently, the lower tail of the outcome distribution shifts as a consequence of the transfer program, then the upper tail does follow.

3 Linkages Along the Village Welfare Distribution

3.1 Credit & Insurance Market Linkages

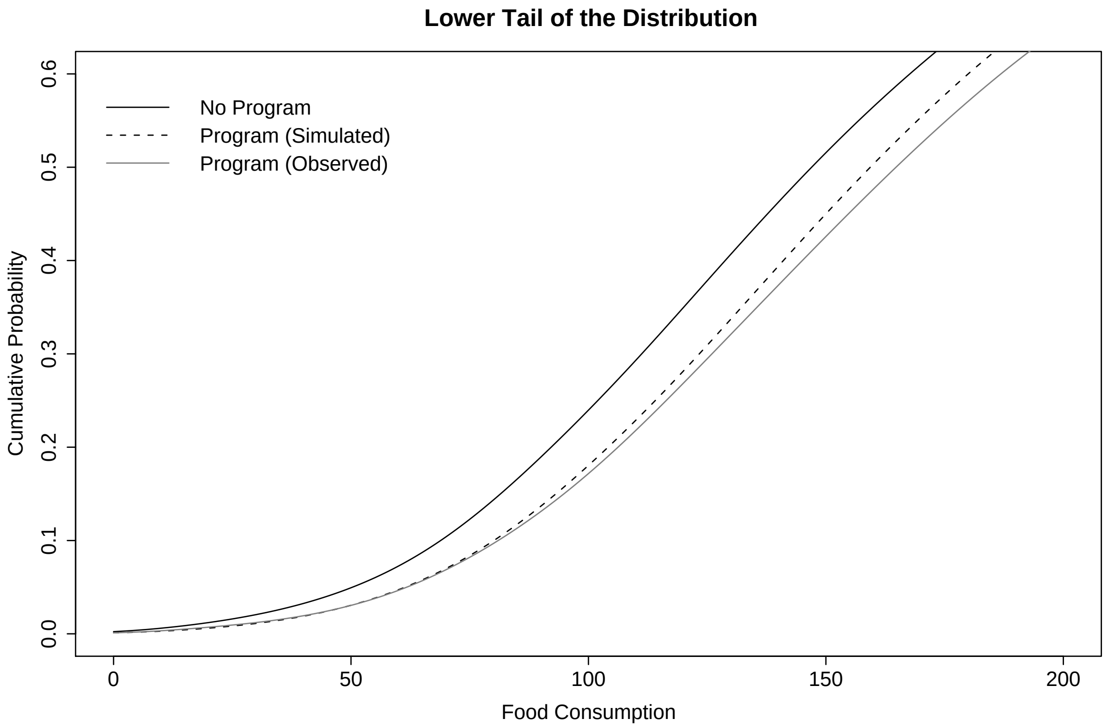
In many agrarian village economies, households are subject to a number of potential consumption shocks.[10] Climatic risks (drought, flooding, frost, etc.) and associated harvest failure, but also labour and oxen problems (diseases, deaths), as well as land problems (villagisation, land reform) are some of the frequent risks these households are facing (Der-

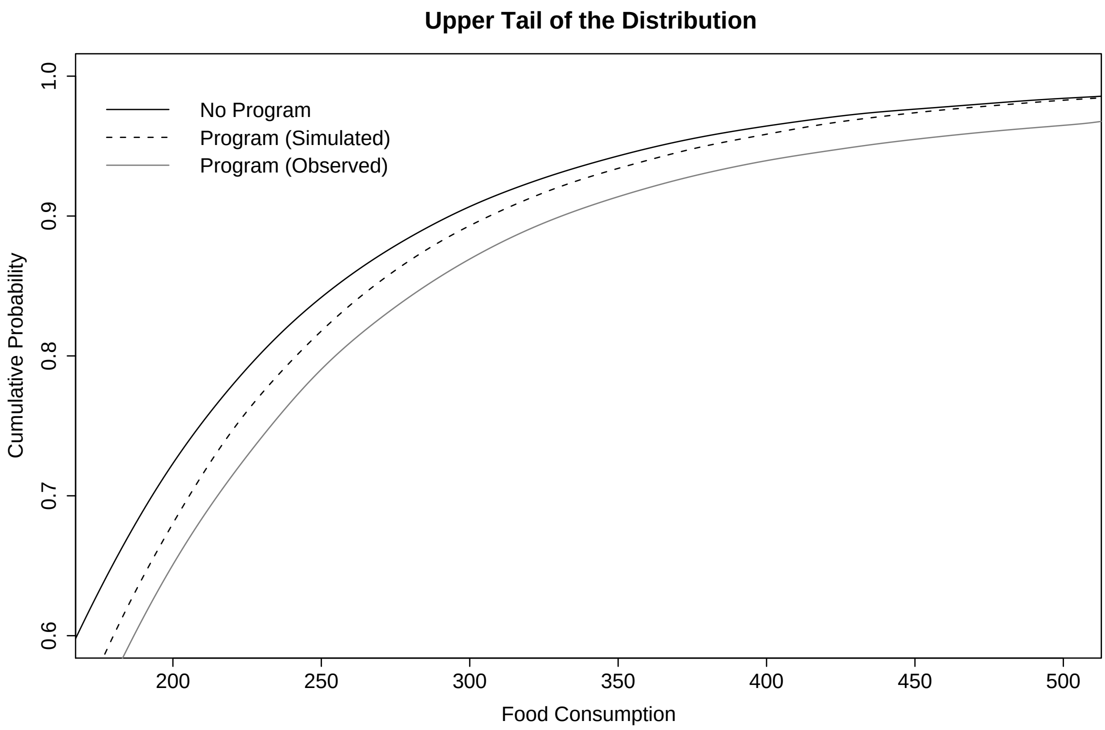
[8] Our result are consistent with the findings of Angelucci and De Giorgi (2009).

[9] We do find a similar pattern when considering income (plus value of consumed own agricultural production) as outcome variable (see figure 3 in the appendix).

[10] Jacoby and Skoufias (1997), Pallage and Robe (2003), Grimard (1997)

Figure 2: Cumulative Distribution Functions





con, 2002).[11] Yet, despite the apparent need of households to smooth income fluctuations, *formal* financial and insurance markets for even the most prevalent risks are often deficient. That is why *informal* insurance arrangements are particularly prevalent. The literature on informal risk insurance stresses that informal in-kind gifts to other community members, based on the principle of reciprocity, is among the most common informal insurance strategies (Fafchamps, 1992). The simplest form of reciprocity is a norm of sharing and gifting (Cashdan, 1985). The gift recipient is often not expected to give back something equivalent to what is received, but rather to help whenever the donor is in need.

Rosenzweig (1988) suggests that such informal insurance arrangements operate along the village welfare distribution. He argues that income streams of involved parties must differ in order to make informal reciprocity insurance arrangements an optimal strategy for both parties involved. Because if the insurance parties would come from the same point at the village welfare distribution, i.e have identical income streams, then neither party would be able to smooth the others consumption when a covariate shock (for example harvest failure) hits. Both parties are always equally affected and hence unable to help smoothing the other's consumption stream. It is therefore optimal for households to seek informal insurance arrangements with households that are located at a different position in the village income distribution. This implies that the lower tail of the village welfare distribution reallocates a part of the government monetary transfer to the upper tail of the village welfare distribution.

Taking the example of the Mexican *Progresa* program, Angelucci and De Giorgi (2009) explore such credit and insurance markets linkages between lower and upper tail. Their findings imply that the lower tail of the village welfare distribution reallocates part of the transfer to the upper tail in form of credit and/or gifts. The authors further argue that this increased availability of insurance for the upper tail induces the latter to consume now redundant precautionary in-kind savings. The latter leads to permanent increases in food consumption levels.

[11]High income variability related to risks of various forms have been investigated by Townsend (1994) for India using the 10-year panel data for one of three ICRISAT villages in India. He finds high yearly fluctuations yields (in monetary terms) per unit of land for the dominant crops. Kinsey et al. (1998) analyze the frequency of harvest failures in a 23-year panel of rural households in a resettlement area in Zimbabwe and find high fluctuations. Dercon (2002)and Morduch (1995) provide more examples.

3.2 Commodity Market Linkages

Apart from linkages in credit and insurance markets, we'll argue that linkages in commodity markets are equally important in explaining why the program-ineligible upper tail of the village welfare distribution does follow the transfer-receiving lower tail: government transfers granted to the lower tail increases the latter's demand for both agricultural and non-agricultural commodities. Due to production-capacity constraints of the village a large proportion of the demand increase is met through village imports. The program-ineligble upper tail of the village welfare distribution, in turn, accrues additional income from supplying these commodities to the lower tail.

Increase in Village Imports

The average village size in our sample of 506 survey villages is 45 households. On average 60 percent households in village are classified as 'poor' by the Mexican government and hence do qualify for the transfer program. Lehmann (2010) reports that, one year after the start of the program, monthly per capita household food consumption for a household residing in a treatment village is, on average, 19 Peso higher compared to control villages. In order to see how much of the latter is met through village imports Lehmann (2010) calculates for each of the 506 villages of the sample, the difference between the sum of village resident's food purchases and sales of resident's own agricultural production. Lehmann then regresses this difference on the treatment status of a village. The result is a lower bound estimate of the program effect on village food imports.[12] Lehmann's findings suggest that fourteen out of the 19 Peso increase in food consumption is met by village food imports.

Imports are not limited to only food. In table 5 in the appendix we report increases in consumption of other goods that are usually not produced by the village. The table shows that households spent a significant proportion of the government transfer on household supplies (pans etc.), shoes and clothing, as well as toys and school supplies for children.

Income Increase from Sales of Imported Products

The import process is a linkage function between the lower and upper tail of the village welfare distribution. The program-ineligible upper tail may benefit through appropriating value-added from the import process.

[12]The estimate is a lower bound estimate because villagers can also realize sales of own agricultural production outside the village (exports). The higher the amount of village food exports, the more we are underestimating the program effect on village food imports.

Table 3: OLS Regression on pre-program asset index: Dependent variable is Pr[selling retail commodities] and profits from sales of retail commodities (in Mexican Peso), respectively.

	Pr[selling retail commodities]		Profits [retail commodities]	
	OLS	Probit	OLS	Tobit
Pre-Program Asset Index	.005***	.039***	24.91*	177.49***
	[.002]	[.014]	[13.58]	[40.39]
Controls	YES	YES	YES	YES
n	19,989	19,989	19,989	19989

Notes: *Significant at 10%; **significant at 5%; ***significant at 1%. Standard errors are clustered at the village level. The wealth index is the first principal component of a vector of household durables (car, material of floor, etc.) measured prior to the start of the program.

How does the import process looks like in Mexican villages? Field visits by the author to around 30 rural villages in February 2010 revealed that village imports are mainly sourced from the state capital. The costs of reaching the state capital are usually substantial for a household belonging to the lower tail of the village welfare distribution. That is why a product is usually not imported by the end-consumer but rather by some village resident who acts as intermediary. This 'retail seller' purchases a certain amount of a product in the state capital and sells it with a mark-up in the village.
Who engages in such kind of commercial import activities, the upper or the lower tail of the village welfare distribution? Let I_i^{re} take the value one if a household sells products that neither stem from its own agricultural production nor were manufactured by the household. We will refer to this type of commodities as 'retail commodities'. Let Y_i^{re} be in the profits derived from sales of such commodities. In Table 3 we report the results of regressing I_i^{re} and Y_i^{re} on a pre-program household wealth index[13] and a vector of controls, respectively. Our results suggest that a household located at the upper tail of the village wealth distribution is a) more likely to sell 'retail commodities' and b) derives higher profit from such sales.

Consequently, we'd expect the upper tail of the village welfare distribution to accrue additional income from the program induced raise in demand for imported commodities. Table 4 reports the difference in profits

[13]The wealth index is the first principal component of a vector of household durables (car, material of floor, etc.).

Table 4: OLS Regression results: Changes in retail business activity of non-beneficiaries in treatment villages

	profits	Pr[selling retail products]	work hours/day	work days/month
	Tobit	OLS	Tobit	Tobit
Residing in treatment village	83.12*	.019**	1.48*	7.24**
	[47.84]	[.008]	[.86]	[3.02]
Controls	YES	YES	YES	YES
n	4,630	4,515	4,495	4,495

Notes: *Significant at 10%; **significant at 5%; ***significant at 1%. Standard errors are reported in parenthesis. Only program-ineligible households are included in the regression.

from sales of 'retail commodities' of program-ineligible households (i.e. located at the upper tail of the village welfare distribution) in treatment versus control villages. We find that ineligible households in treatment villages make 83.12 Peso/month more profit. This is roughly seven percent of the average household income of program-ineligible households. Table 4 further shows that program-ineligible households allocate more labor to selling retail products. On average, ineligible households in treatment villages work $1\frac{1}{2}$ hours more per day, and about seven days more per month to such selling activities.

4 Conclusion

High levels of inequality are a persistent feature of many rural areas in the developing world. Inequality is correlated with major impediments of rural development, such as crime, elite-capture, and lack of collective action. Government transfer programs, such as conditional cash transfer, unemployment insurance, old-age pension or similar programs that target the lower tail of a village's welfare distribution have become a very popular public policy to tackle poverty and inequality in rural areas. While the poverty impacts of those programs are well documented in the literature less attention has been given to the redistributive capacity of such policies at the village level. Among the main reasons for the neglect is a common belief that monetary transfers to the lower tail of the village welfare distribution (i.e. 'the poor'), while excluding the upper tail (i.e. 'the non-poor') from the program, must lead to a reduction in inequality. In this paper we showed that the impact of such programs on reducing rural inequality may be lower than previously thought. This is because program-eligible lower and program-ineligible upper tail do not behave in isolation from each other. They are linked via interactions in credit & insurance, as well as factor & commodity markets. Taking the example of a Mexican transfer program, we bring suggestive evidence for linkages in the commodity market. The transfer program leads to increased village imports. The 'better-off' households in the village, i.e. the program-ineligible upper tail of the village welfare distribution, have the necessary asset endowments to engage in such import/retail trade activities. The upper tail benefit's by deriving more income from sales of products that do neither stem from own agricultural production nor are manufactured by the household.

Our results imply that government transfer policies in village economies do have local multiplier effects. The gains of these multiplier effects seem to be accrued by the upper tail of the village welfare distribution.

From a public policy evaluation perspective, our results imply that impact evaluations which disregard linkages between the program-eligible lower and program-ineligible upper tail may underestimate the overall impact of the program on poverty. This is because in many cases funding for a transfer program is limited. Therefore, governments oftentimes allocate the transfer to the most vulnerable subset of the population, i.e. the very lower tail of the village cumulative welfare distribution function. However, those deemed 'ineligible' for the program oftentimes are far from what one would consider 'well-off'. For example, the monetary value of ineligibles' daily per capita food consumption in Mexico's *Progresa* program was below one US Dollar when the program started in 1997. Thus, poverty often persists even among the program-ineligible upper tail of the village welfare cumulative distribution function. In the presence of credit & insurance, as well as factor & commodity markets linkages between lower and upper tail of the distribution, an evaluation that focuses exclusively on the part of the distribution that has been granted the government transfer may underestimate the overall program impact on village poverty.
Our results further imply that static microsimulations (see for example Bourguignon and Spadaro (2006)) may yield inaccurate predictions of distributional impacts of government transfer programs in rural areas. Incorporating interactions of program-eligible lower and program-ineligible upper tail via credit & insurance, as well as factor & commodity markets into a microsimulation frameworks remains thus a fruitful avenue for future research.

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5 Appendix

5.1 Microsimulation

In a first step, we estimate inequality measures for food consumption in each control village. In a second step, we add the monetary transfer to household income of each eligible household in the control group, then estimate the change in food consumption based on the elasticity of food consumption with respect to income, and finally calculate again inequality measures for food consumption in each control village. In a third step, we calculate the difference between the inequality measures obtained in step one and step two. In the following, we will describe these steps in more detail

Step 1: Inequality in control villages, before the monetary transfer
Let j be index for villages in the sample. In a first step, we obtain an estimate for the level of inequality in control village, denoted $\nu_j(F_{Y(0)})|P_j = 0]$, using the inequality measures defined in equations 2 to 1.

Step 2: Inequality in control villages, after introducing the monetary transfer
Since the cash transfer depends on the schooling choice of the household (i.e. the more household members enrolled the higher the monetary transfer), we first have to estimate the change in a household's schooling choice when facing the opportunity of the monetary transfer. This allows us to determine the magnitude of the monetary transfer for each program-eligible household in the control group. We follow Bourguignon et al. (2003) and model the enrollment choice of household in a multinomial logit framework whereby S_i is a qualitative variable that takes the value zero if the child works full-time, one if the child works goes to school and works outside the household, and two if the school attends school and does not work outside the household. The household chooses

$$S_i = k \text{ if } V_k[x_i', h_i', Y_{-i}+y_{ik}(w_i)]+\nu_i k \; > \; V_j[x_i', h_i', Y_{-i}+y_{ij}(w_i)]+\nu_i j \text{ for } j \neq k \tag{9}$$

where V_j is a latent function describing the household's utility when choosing alternative $j \in 1, 2, 3$, and x_i' and h_i' being a vector of child and household characteristics, respectively. Y_{-i} is household income without the child's contribution, y_{ij} is assumed to be the child's output of both market and domestic child labor in occupational choice j as a function of the child's market earnings w_i, and ν_{ij} being a random variable that captures unobserved heterogeneity. The latent function V_j is assumed to be linear in its component x_i',h_i', and $Y_{-i} + y_{ij}(w_i)$:

$$U_i(j) = V_j[x_i', h_i', Y_{-i}+y_{ij}(w_i)]+\nu_{ij} = z_i'\gamma_j+[Y_{-j}+y_{ij}(w_i)]\alpha_j+\nu_{ij} \quad (10)$$

The potential child earnings are imputed as

$$log\, w_i = x_i'\delta + m \cdot \rho\mathbf{I}[S_i = 1] + \varepsilon_i \quad (11)$$

where x_i' is a vector of child characteristics (age, schooling, etc.) and ε_i being a random term capturing unobserved earning determinants. $\mathbf{I}[\cdot]$ is an indicator function that takes the value one if the child goes to school and works outside the household. The child's contribution to household income for the three occupational states is then defined as

$$y_{i0} = Kw_i; \quad y_{i1} = My_{i0}; \quad y_{i2} = Dyi0 \quad \text{with } M = \exp\rho \quad (12)$$

with y_{ij} assumed to measure the output of both market and domestic child labor. Hence, domestic child labor income is proportional to actual or potential market earnings w_i in a proportion K for people that do not attend attend school. Going to school while working outside the household reduces the child's contribution by (1-M) percent, compared to a non-enrolled child. Going to school without working outside the household reduces the child's contribution by (1-D) percent, compared to a non-enrolled child. The proportions K and D are not observed. The proportion M is taken to be the same for domestic and market work and may be estimated based on the child's earning equation. Substituting yields

$$U_i(j) = V_j[x_i', h_i', Y_{-i} + y_{ij}(w_i)] + \nu_{ij} = z_i'\gamma_j + Y_{-j}\alpha_j + \beta_j\, w_i + \nu_{ij} \quad (13)$$

with $\beta_0 = \alpha_0 K$, $\beta_1 = \alpha_1\, M\, K$, and $\beta_2 = \alpha_2\, D\, K$. Now, the monetary transfer would effect household utility in the following way:

$$U_i(j) = z_i'\gamma_j + (Y_{-j} + \tau_i^{nut} + \tau_{ij}^{school})\alpha_j + \beta_j\, w_i + \nu_{ij} \quad (14)$$

where τ_i^{nut} is the component of the monetary transfer that is independent of the schooling choice, and τ_{ij}^{school} the component that depends on a household's schooling choice. Program eligible is defined by a household's level of household welfare, denoted Φ_i. If the household's welfare is above the programs eligibility cut-off, $\underline{\Phi}_i$, then the household is not eligible for any of the two monetary transfer components:

$$\tau_i^{nut} = \tau_{ij}^{school} = 0 \;\text{ if } \Phi_i > \underline{\Phi}_i \quad (15)$$

If the household's welfare is below the cut-off, the it receives a nutrition monetary transfer with value $x \in \mathbb{R}^n_+$,

$$\tau_i^{nut} \in \mathbb{R}^n_+ \text{ if } \Phi_i \leq \underline{\Phi}_i \tag{16}$$

and a schooling monetary transfer that depends on the enrollment choice

$$\tau_i^{school} \begin{cases} \in \mathbb{R}^n_+ & \text{if } j = 2, 3, \Phi_i \leq \underline{\Phi}_i \\ 0 & \text{if } j = 1, \Phi_i \leq \underline{\Phi}_i \end{cases} \tag{17}$$

with the exact value of the schooling component on gender, and grade of enrolled members of eligible households. The household then chooses the alternative that maximizes household utility:

$$k_i^* = arg\ max[U_i(j)] \tag{18}$$

We refer the reader to Bourguignon et al. (2003) for a description of the multinomial logit simulation procedure that yields the optimal schooling choice k_i^* of the household i.

Having obtained an estimate of the schooling choice of the eligible households, we are then able to calculate the amount of the monetary transfer for each eligible household i:

$$\tau_i = \tau_i^{nut} + \tau_i^{school}(k_i^*) \tag{19}$$

Having obtained the transfer amount, τ_i, we are then able to simulate the effect of the monetary transfer on food consumption. Our reduced form model for food consumption is

$$c_i = \alpha_0 + \alpha_1 y_i + x_i'\beta + \epsilon_i \tag{20}$$

where c_i is monthly per capita food consumption (monetary value) of household i. The variable y_i denotes household income, and x_i' is a vector of household characteristics. We estimate the this equation with OLS to obtain estimates of α_0, α_1, β and ϵ_i. We then add the monetary transfer to household income and predict the new value of food consumption by

$$\hat{c}_i = \hat{\alpha}_0 + \hat{\alpha}_1(y_i + \tau_i) + x_i'\hat{\beta} + \hat{\epsilon}_i \tag{21}$$

Step 3: The simulated average inequality treatment effect in the absence of 'spill-over' effects

We then obtain an estimate for the level of inequality in control village after the monetary transfer τ, denoted $\nu_j(F_{Y(0)+\tau})|D = 0]$, using the inequality measures defined in equations 2 and 1.

$$\widehat{AIE}_2 = E[\nu_j(F_{Y(0)})|P_j = 0] - E[\nu_j(F_{Y(0)+\tau})|P_j = 0] \qquad (22)$$

which is obtained by the following OLS regression on control villages ($D_j = 0$):

$$\nu_j = \alpha_0 + \theta_2 t_j + \beta z'_j + u_j \qquad , \text{if} \;\; D_j = 0 \qquad (23)$$

where t is a dummy taking the value one for $\nu_j(F_{Y(0)})|P_j = 0$ (i.e. before the monetary transfer), and zero for $\nu_j(F_{Y(0)+\tau})|P_j = 0]$ (i.e. after the monetary transfer). θ_2 is an estimator of the AIE in the absence of 'spill-over' on the program-ineligible upper tail of the village welfare distribution.

5.2 Tables

Table 5: Program effects on transfer recipient households (log) expenditures for non-food items (estimated one year after the start of the program).

	Treatment-Control [se]
Hygiene	.085***
	[.042]
Household utilities supplies	.222***
	[.044]
Toys	.102***
	[.022]
Cloth	.610***
	[.090]
Shoes	.557***
	[.089]
School supplies	0.275***
	[0.047]

Notes: *Significant at 10%; **significant at 5%; ***significant at 1%. We drop the 99 percentile of each variable. Standard errors are clustered at the village level.

Figure 3: Cumulative Distribution Function