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Social Protection and Inequality: Evidence from Ethiopia, India and Peru

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Résumé

Nous étudions l'impact de trois programmes de protection sociale àgrande échelle sur les inégalités entre et au sein de groupes socialement et culturellement construits en Éthiopie, en Inde et au Pérou. Àl'aide des données en panel du projet Young Lives, nous analysons les tendances et les évolutions des inégalités verticales et horizontales dans les trois pays avant et après la mise en œuvre des programmes. Nos résultats montrent une forte corrélation entre le niveau de vie et la couverture du programme de protection sociale, et par conséquent des inégalités plus faibles entre les participants au programme. Une analyse de décomposition montre que les inégalités au sein du groupe expliquent une grande proportion des inégalités totales dans tous les échantillons en considération.

Abstract

We investigate the role of three large-scale social-protection schemes in Ethiopia, India, and Peru on inequalities among and within socially- and culturally-constructed groups. Using data from the Young Lives cohort study, we analyse the trend, changes and evolution of vertical and horizontal inequality in these three countries before and after program implementation. Our findings show a strong correlation between living standards and social-protection program coverage, and subsequently lower inequality among program participants. Decomposition analysis shows that within-group inequality accounts for the largest part of total inequality in all the samples we considered.

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Mots-clés: Protection sociale; inégalités horizontales; analyse de décomposition; PSNP; NREGS; Juntos; Young Lives.

Keywords: Social protection; horizontal inequality; decomposition analysis; PSNP; NREGS; Juntos; Young lives.

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Introduction

A growing body of recent literature has shed new light on the extent to which inequalities run along ethnic, gender, and other communal lines, as well as the understanding of the determinants of these group-based inequalities, including the potential for policy intervention. Inequality between ethnic groups has major socioeconomic implications, such as conflicts (Cederman et al., 2011), the under-provision of public goods (Alesina et al., 2016; Banerjee et al., 2005), poverty reduction (Dang, 2019), and inequitable economic outcomes (Chadha and Nandwani, 2018).

Most evaluations of social-protection programs have focused on estimating the programs' effects on education, health, consumption, and labor market outcomes (Afridi et al., 2016; Imbert and Papp, 2015; Zimmermann, 2014; Angelucci and De Giorgi, 2009; Bose, 2017). There is less work on these outcomes using a distributive lens. One potential reason for the limited distributional evaluation is that social-protection programs, by design, target the poor. This particular feature restricts the findings from any distributive analysis on social protection to the lower end of the consumption distribution (Ham, 2014).

There is also the implicit assumption evident in most of the literature on the impact assessment of antipoverty programs that pro-poor programs are necessarily inequality-reducing or that the programs are sufficiently successful in containing the social tensions that would follow from increasing inequality. However, this is not necessarily the case. A lower poverty headcount is consistent with the poorest of the poor being left behind, and a drop in overall inequality might mask different fates for various social groups.

In this study, we attempt to fill some of the evidence gap and add to the literature by evaluating the role of three large-scale social-protection programs on inequality. We examine the changes in consumption inequality among culturally- and socially-defined groups in Ethiopia, India and Peru over the 2006-2016 period. We use a unique longitudinal data set with information on participation in national social-protection schemes: the Productive Safety Net Program (PSNP) in Ethiopia, the National Rural Employment Guarantee Scheme (NREGA) in India, and the *Juntos* conditional cash-transfer program in Peru. These programs were put in place more or less at the same time, and reached a significant proportion of the population. However, their design and the targeting mechanisms are not the same: from a cash-for-work program based on self-selection in India to a cash-transfer program based on direct household targeting in Peru, with Ethiopia occupying a middling position (the PNSP uses direct transfers as well as food-for-work, and targets both geographical areas and individuals).

There are important socio-economic differences between pre-existing social and ethnic groups in all three countries, although each one has its own idiosyncratic experience. We document the evolution of between- and within-group inequality among ethnic and religious partitions of the population. We further decompose group differentials into the part explained by mean differences in covariates, and an unexplained part reflecting "structural" differences between ethnic and religious groups (the Oaxaca-Blinder decomposition). Finally, we follow the decomposition approach proposed by Cowell and Fiorio (2011) to understand the contributions of the relevant factors to within-group inequality.

We have a number of key findings. First, there is a strong correlation between living standards and social-protection program coverage, indicating positive targeting efficiency. We also find that inequality among program participants is much lower than among non-participants. Second, a decomposition of total inequality shows that within-group inequality consistently accounts for a larger share of total inequality for all groups considered.

Regarding the evolution of between-group inequality, we find different patterns in all three countries. Ethiopia is characterized by a reduction in between-group inequality; the decompositions suggest that this reduction is limited to some ethnic groups. However, the detailed decompositions suggest that the PSNP had a significant, albeit quantitatively-limited, role to play in this reduction of differentials between groups. Between-group inequality is increasing in India; this mostly reflects the so-called "Backward Castes"converging with the "Other Castes", while some groups (Scheduled Castes and Scheduled Tribes) are increasingly marginalized. We do not find a significant contribution of the NREGA to the reduction of between group-differentials. Finally, the difference between groups seems to decrease over time in Peru, from an already low level. The existing differences are mostly due to differences in observable characteristics.

The remainder of the paper is organized as follows. In Section 1 we outline the theoretical link between inequality, poverty reduction, and social protection in a brief conceptual framework. Section 2 is devoted to the introduction of the institutional framework of our study context. We describe the dataset and outline our empirical strategy in Section 3. Results are presented in section 4, and discussed, along with policy implications, in Section 5. Section 5 concludes.

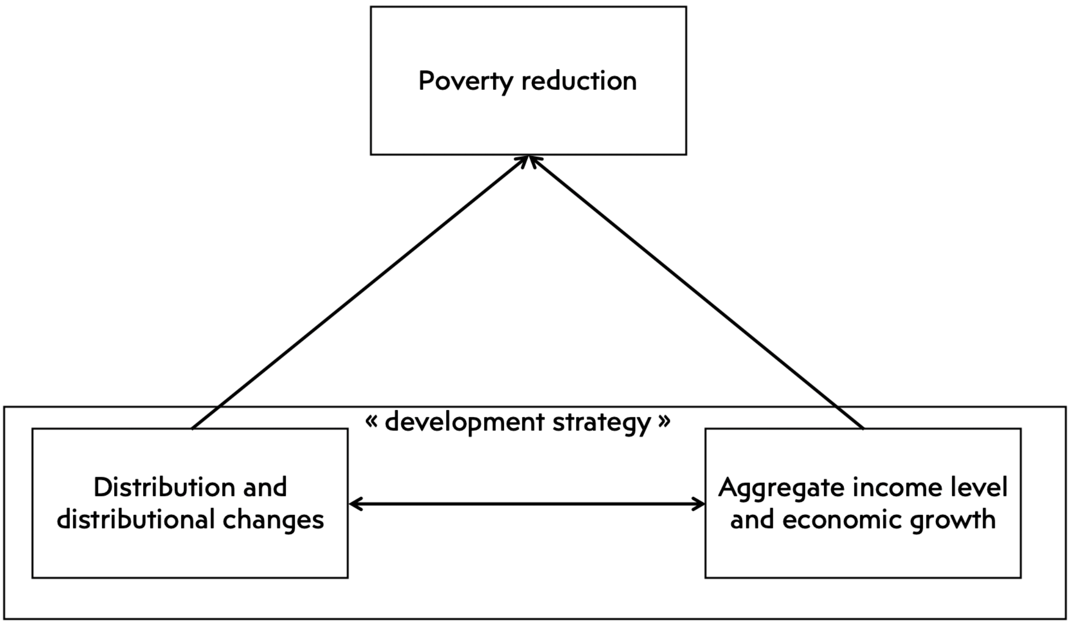
1. Conceptual framework

1.1. The link between inequality, poverty reduction, and social protection

On the simplest conceptual level, there is positive relation between inequality and poverty: everything else equal, a more equal distribution of income generated by trasfers from non-poor to poor individuals reduces poverty. However, absolute poverty can also fall due to growth: if all incomes rise at the same rate, (relative) inequality will remain unchanged, and absolute poverty will fall (Kanbur, 2000).

Taking into account the influence of economic growth on inequality and poverty leads to the so-called “Bourguignon triangle” (Fig. 1, after Bourguignon, 2004), which summarizes the relations between these three factors. Economic growth can affect the income distribution, but there is no systematic rule regarding the size and sign of the impact: economists no longer believe in mechanistic relations such as the “Kuznets hypothesis” of an inverted-U relationship between growth and inequality (Kanbur, 2000). The implication is that there is ample room for policy intervention in shaping the distributional consequences of growth episodes (Bourguignon, 2004).

Figure 1: The “Bourguignon triangle”



Source Bourguignon (2004).

There may equally be a negative causal link in the other direction, from inequality to growth: high levels of inequality might hamper growth, for instance by causing social unrest, political instability, or by promoting elite capture. By implication, inequality-reduction policies may have a “double dividend” in terms of poverty reduction: first in the present period, through the mechanical link between inequality and poverty; second in the future, if lower inequality leads to higher growth, which in turn reduces poverty.[1] Hence, at least in principle, a social-protection program should act as a mediator in the "growth – inequality" part of the triangle, producing a lower level of inequality for a given rate of growth.

While some inequality reduction is associated with lower poverty, we can ask if there is a causal link in the opposite direction, from poverty to inequality? On the conceptual level, a reduction in the poverty headcount does not always imply lower inequality: regressive transfers from the very poor to individuals who are located just below the poverty line might simultaneously produce higher inequality but a lower poverty headcount. (Deaton, 1997).

In practice, even in the absence of regressive transfers, a reduction in poverty thanks to a particular policy might not be accompanied by lower inequality. The poverty reduction might be too small to affect overall inequality. Alternatively, greater inequality may come about for independent reasons, counterbalancing the inequality-reducing effects of the policy. Note that these are issues linked with causal inference and counterfactual reasoning. If a policy reduces poverty, without any regressive transfers between the poor, inequality would indeed be greater in the absence of the policy. The fact that inequality does not seem to fall points towards either an expansion of the size of the program or the need to put in place independent policies to deal with the root cause of greater inequality.

Horizontal inequality and between-group differences

The preceding discussion implicitly assumes that the individual or the household is the relevant unit for the evaluation of the changes in income distribution. One way of rationalizing the well-known Gini index is as an average of all the income differences within one country. This view is indebted to classic individualistic utilitarism Kanbur (2000): every individual/household is its own group, and evaluates its situation with regards to the whole of society. However, a rich theoretical and empirical literature has shown that group attachment matters for the evaluation of individual wellbeing, something that is not recognized by common indicators.

In the field of development economics, a particular focus of attention is the link between ethnic fractionalization and conflicts (Cederman et al., 2011). It is all the more relevant to look at the evolution of inter-group inequality as the evolution of overall indicators is a "net" phenomenon that may mask a number of different factors that push in different directions. As noted by Kanbur (2000), there is a multitude of winners and losers behind the evolution the overall distribution of income, and the fact that the gains of the former exceed the losses of the latter does not guarantee the absence of social tensions. This is especially the case if the losers are concentrated in an existing social group, such as an ethnic group, which might make collective-action problem easier to overcome. One example of this scenario is the opening to external competition that reduces price of the relatively-scarce production factor; if this factor is predominantly owned by one group, this group might organize to prevent foreseeable losses due to the liberalization, even though society as a whole might be richer and more equal as a result.

[1] The "growth – inequality" pair are dubbed "development strategy" by Bourguignon in his original paper.

1.2. Design issues: What form should social safety nets take?

Social policy is key for the management of the distributional consequences of a development strategy. Up until the 2000s, the conventional wisdom was that direct redistribution through the tax and transfer system, although desirable, was difficult to implement in the developing-country context due to low administrative capacity and the limited observability of incomes (Kanbur, 2000). The explosion of safety nets in the developing world since this time argues against this position (Ivaschenko et al., 2018). These policies are not one size fits all, and their design varies widely (Marx et al., 2015). In this section, we discuss briefly two issues regarding the design of social-safety nets in low- and middle-income countries.

The selection of beneficiaries: narrow vs. categorical targeting

It is generally assumed that most developing countries do not have the fiscal space and/or administrative capacity to carry out universal transfers.[2] Some form of selection of beneficiaries is necessary. But what form should this take? The debate can be summarized by the opposition between "narrow targeting" via proxy means testing on the one hand, and categorical or geographical targeting on the other hand. Proxy means tests (PMT) allocate the benefits of a given program to individuals or households based on their *predicted* poverty, which itself is calculated by a score based on the household's living conditions and durable-goods possession. In contrast, in the case of geographical targeting, everybody in a given area is eligible for the benefits; categorical targeting reserves the programs to certain categories of at-risk people (e.g. pregnant women or the elderly). In practice, real-world social-safety nets in developing countries take an intermediary position, such as Ethiopia's PNSP that makes use of a geographical criterion on top of a formula that targets households.

In theory, narrow targeting maximizes the poverty-reduction impact of a given antipoverty policy, by concentrating the benefits on the neediest (Grosh et al., 2008). However, this kind of targeting has a number of drawbacks in practice. First, targeting through proxy means tests is intrinsically imprecise and prone to error. Brown et al. (2018) show, in the context of Sub-Saharan Africa, that this targeting is far better at excluding the non-poor that it is at selecting the poor, and that it is especially bad at reaching the poorest. The frequent need for recertification and intrusive data collection have fuelled suspicions that proxy means targeting is contributing to unrest and the degradation of social ties (Cameron and Shah, 2014). Finally, narrowly-targeted policies tend to be less popular than policies that allow for some leakage of benefits to the non-poor. This is the "paradox of redistribution", frequently observed in the developed-country context, whereby "policies reserved to the poor tend to become poor policies" (Marx et al., 2015). However, it is not clear what the alternatives to a targeted policy are, so that future efforts might focus on the amelioration of existing targeting systems, rather than a complete overhaul (Hanna and Olken, 2018).

[2] For a dissenting point of view, see Banerjee et al. (2019).

Workfare vs. welfare

The main attraction of workfare (also known as public-works programs or cash-for-work) is that, thanks to their work requirement, they entail a self-selection of the neediest beneficiaries (Besley and Coate, 1992), thus sidestepping the difficult issue of having to decide who is poor and who is not in a context where resources are unobservable. The work requirement of workfare typically consists of physically-difficult jobs, paid at low wage rates: only those who really need the help will register for the program. This work requirement might also enhance the political acceptability of such schemes. While direct transfers are often misconstrued in the public debate as "handouts", the benefits from cash-for-work schemes give the impression of being "deserved" by their recipients. Finally, cash-for-work may contribute to the construction of valuable infrastructure, which may, in case of a positive effect on productivity, yield a "double dividend" in terms of poverty reduction. These advantages presumably explain the enduring popularity of cash-for-work schemes in the developing world.

Workfare is not without drawbacks, however. First, by nature, they often exclude certain categories of beneficiaries, most notably the elderly or nursing women. Cash-for-work schemes tend to have higher overhead costs, due the inputs and the qualified labor necessary to run the project (Banerjee et al., 2019). On a conceptual level, a complete comparison between workfare and direct transfers should take into account the disutility of work experienced by the workfare participants, as well as psychological costs due to social stigma (Ravallion, 2019).

Recent empirical work has questioned the putative advantages of workfare over welfare. Bertrand et al. (2017), using machine-learning techniques in the context of the randomized trial of a public-works program in Côte d'Ivoire, show that the gains from self-targeting are probably smaller than previously thought due to trade-offs with the size of the individual impact: if one wants to achieve efficiency in targeting through workfare projects, the benefits have to be set at a low level close to the subsistence line; if one wants to achieve substantial poverty reduction, one has to accept a certain level of mistargeting. On the political-economy front, work in the context of India's NREGA has shown that the largest impact of the program occurs through its (external) effect on the wages of unskilled workers (Muralidharan et al., 2017; Imbert and Papp, 2015). This implies that large-scale workfare programs are not Pareto improvements, but have large distributive effects at the local community level: unskilled workers gain, and hirers of labor (typically landowners) stand to lose, which explains why NREGA suffered intense political opposition when it was generalized.

With respect to the dataset used in this paper, the countries under consideration use various methods of targeting to allocate the benefits of their respective social policies. Peru's *Juntos* is attributed on the basis of household characteristics, according to a complicated formula (72 variables are necessary, with a recertification of beneficiary households every three years. See Hanna and Olken, 2018). India's NREGA program is a quasi-universal cash-for-work program, and hence based on the self-selection of beneficiaries; last, Ethiopia's PSNP combines geographical targeting with the direct targeting of households. The next section presents these programs in more detail.

2. Study Context

We examine the effects of three large-scale social-protection programs in reducing inequalities to provide a holistic understanding on the drivers and consequences of inequalities and how they are influenced by public policies. We chose these programs for a number of reasons. First, they are very large projects that involve a coordinated effort of governments, donors local authorities and individual households. Second, the programs cover three countries that uniquely offer diverse social, cultural, political, and economic context from which lessons can be drawn. Third, the assessment will provide a rich knowledge and understanding of the targeting, incidence, and heterogeneity of effects of the programs on which future policies can be based.

2.1. The Programs

PSNP: The Productive Safety Net Program (PSNP) is a public program that started in 2005 by the government of Ethiopia and a consortium of donors as a safety net, targeting transfers to poor households through either public works or direct support. The aim is to enable households smooth consumption without the need to sell productive assets in lean periods. The public works segment of the program pays selected beneficiaries for their labor on labor-intensive projects designed to build community assets. In addition, by reducing seasonal liquidity constraints, it is intended to stimulate investments as well (Andersson et al., 2011; Gilligan et al., 2009).

The selection of beneficiaries for both the public works and direct support components of the safety net program uses a mix of administrative criteria and community input. When the program began in 2005, historical data on food aid allocations were used to select beneficiary districts (*woredas*). Within the *woredas*, local administrators selected the chronically food-insecure *kebeles* (lowest administrative unit), assigning the *woreda*'s "PSNP quota" among these areas (Berhane et al., 2014). Eligibility for the PSNP at the household-level focused on the household's chronic history of food need, level of the food gap or unmet need, and household labor available for work. Communities select beneficiaries in collaboration with the *kebeles* refining the selection based on household assets (landholdings), and income from nonagricultural activities and from alternative sources of employment (Gilligan et al., 2009; Berhane et al., 2014).

NREGA: The National Rural Employment Guarantee Act (NREGA) was passed in 2005, and the scheme began to roll-out in February 2006. The act entitles every household in rural India to 100 days of work per year at a state-level minimum wage to rural households willing to supply manual labor on local public works. To obtain work on a project, interested adult applicants lodge an application for a job card at their local *Gram Panchayat* (the lowest government administrative units). Following verification, a job card is issued and workers can start applying for work. If an applicant is not assigned to a project, they are eligible for unemployment compensation. Applicants cannot choose the project (Shah and Steinberg, 2015).

The act was gradually introduced throughout India starting with 200 of the poorest districts in February 2006, extending to 130 districts in April 2007, and to the rest of rural India in April 2008. In the Andhra Pradesh region where our data is from, four of the Young Lives sample districts (comprising 66% of the sample) were covered by the NREGA in the first phase of implementation in 2006 (Dasgupta, 2017).

Juntos: The conditional cash transfer program *Juntos* was established in 2005 targeting poor families mainly in rural areas in Peru. Its geographical coverage has increased gradually over time, after initially serving 70 districts in the southern highlands, to include other areas of the highlands and the Amazonian jungle. *Juntos* eligibility is based on a three stage selection process: selection of eligible districts, selection of eligible households within those districts, and a community level validation. Exposure to violence due to guerrilla activity, poverty level, unmet basic needs, and level of child malnutrition are the main variables considered in district selection. Household eligibility within districts was determined by a proxy means test formula that is computed based on census data. In addition, only households with children under the age of 14 years or at least one pregnant woman were selected. The final stage is a community level validation that was performed by community members, local authorities and representatives of the Ministries of Education and Health. Beneficiary households received transfers of 100 soles (≈ 30 US dollars) each month regardless of household composition, representing about 15% of beneficiary household spending (Andersen et al., 2015; Perova and Vakis, 2012).

The conditions for transfers under *Juntos* depend on the age and eligibility of the participant. Members of households with children younger than five years of age as well as households with a pregnant or lactating woman are required to attend regular health care visits. Children aged between six and 14 years who had not completed primary school are required to attend school at least 85% of the days (Andersen et al., 2015).

2.2. Data

The data for this study are from the *Young Lives Project*, a study tracking the lives of children in four countries: Ethiopia, India (in the states of Andhra Pradesh and Telangana), Peru and Vietnam over a 15-year period. In each study country, the *Young Lives* surveys track 3,000 children in two cohorts. The younger cohort consists of 2,000 children who were born between January 2001 and May 2002; he older cohort consists of approximately 1,000 children from each country born in 1994-95. Five survey waves are currently available: the baseline round in 2002 and four follow-up waves in 2006, 2009, 2013 and 2016.[3]

[3] For a more complete explanation of the sampling procedure, see Escobal and Flores (2008). See also Outes-Leon and Dercon (2008) for attrition analysis, and Barnett et al. (2013) for the overall cohort profile of the Young Lives study.

One of the advantages of the Young Lives data is that it covers a wide range of well-being indicators, including asset holdings, consumption expenditure, physical and emotional health, nutrition, education and material wealth, as well as child-development indicators. This range of well-being indicators is seldom covered in national representative samples, which typically need to narrow their focus towards individuals' ability to access basic services. The longitudinal nature of the data allows us to document the evolution of inequality over time.

Our analysis uses data from the last four waves of the survey (2006-2016). We present summary statistics for the main variables and controls used in the paper in Table 1.

Household Consumption Expenditure: The household questionnaire collects detailed data on expenditures over the last 12 months. The 12-month recall has the disadvantage of recall bias, but this is likely outweighed by the advantage of more-complete reporting compared to diary-based data collection that only records expenditures over a few weeks. Consumption aggregates combine a number of items which can be grouped into food items and non-food items. Most items are similar across the four Young Lives countries. Country-specific food and non-food items were incorporated into the design of the questionnaire, and therefore into the consumption aggregates (Marion, 2018). Aggregate consumption data includes total per capita expenditure, per capita food consumption, and per capita non-food expenditure, all in both nominal and real terms. Food consumption is aggregated based on self-reported food items consumed in the last two weeks from different sources (e.g. purchased, home-produced, from stock).[4] Non-food consumption covers all non-food items, such as expenditure on education, health, clothing and footwear, or other non-food items.

Household wealth index: Household wealth is measured via an index of housing quality, consumer durables, and household services. The housing-quality index is a simple average of bedrooms per person, and indicator variables that take the value of 1 if the quality of the main materials in the dwelling (walls, roof and floor) satisfy basic quality norms. The access to services index is a simple average of indicators such as access to electricity, safe drinking water, sanitation and adequate fuel for cooking. The consumer-durable index is an average of a set of dummy variables for thechousehold member owning at least one of each consumer durable. Assuming that these three indicators are of equal importance, the wealth index is computed as the simple average of the three indices. The index takes on values between 0 and 1, where a higher wealth index indicates higher socio-economic status (Briones, 2017).

Public programs: Households in the sample were asked to describe their participation status in a number of country-specific public programs, including the duration of participation, the type of support and the benefits acquired.

[4]If a festival, wedding, feasting, fasting period or unusual event took place within the last 15 days, the respondent provided information on the household's consumption in the 15 days prior to the event.

Grouping variables: The grouping variable is one of the main considerations in estimating inequality. In our analysis we make an attempt to balance relevant groups with the availability of data and salience of the group. We consider two main dimensions: ethnicity and religion (see Section 3.2 for more details).

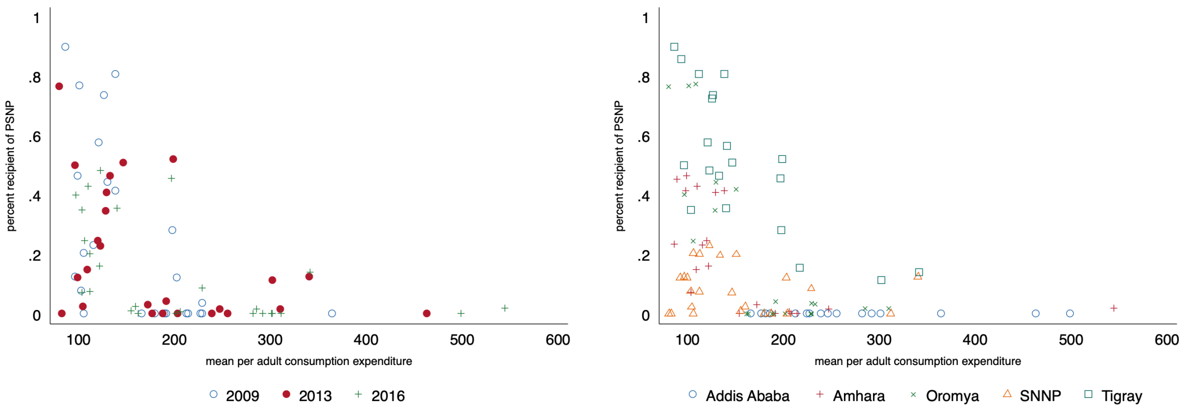
Demographic characteristics: We use the information in the dataset on the characteristics of the household head (age, gender and education), the number of household members by sex and age groups, and the size of the household.

2.3. Targeting

A comprehensive review of antipoverty programs by Coady et al. (2004) finds that interventions that use means testing, geographic targeting, and self-selection based on a work requirement are all associated with an increased share of benefits going to the bottom two quintiles. We begin by assessing the targeting performance of the three social-protection programs in terms of the under-coverage of eligible recipients (errors of exclusion) and leakage of funds to ineligible households (errors of inclusion).

Figures 2 – 4 depict the correlation between the coverage rate and living standards (as measured by real household consumption expenditure). We plot the coverage of the programs across sentinel sites and over three post-program survey waves. For Ethiopia and Peru, there is a considerable degree of variability across sites in terms of the percentage of the population participating in the safety net program under consideration. In India there is only a weakly-negative correlation between the percentage covered and mean expenditure per capita. However, there is wide variation, particularly at low living-standard levels.

Figure 2: Correlation between PSNP coverage and consumption



(a) Coverage by survey year **(b) Coverage by region**

There is some variation in regional coverage in Ethiopia (Figure 2b), where the Tigray region

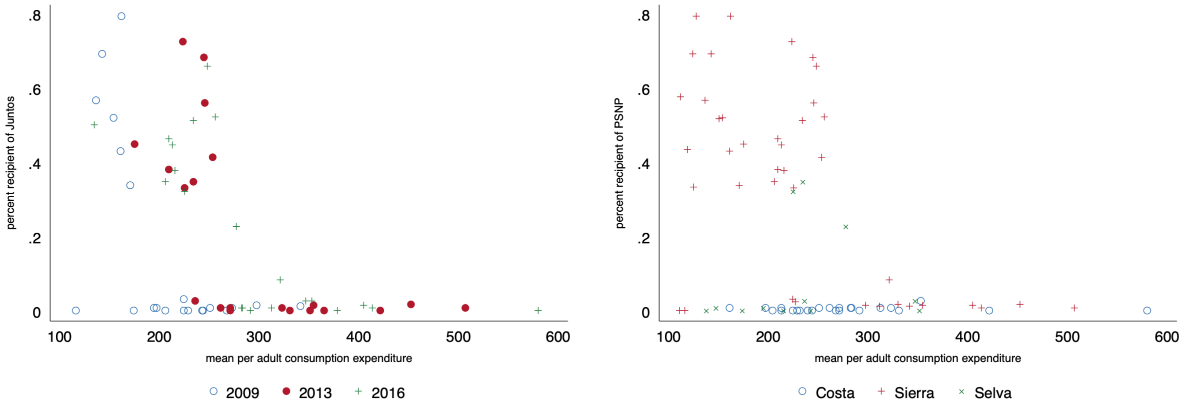
Table 1: Summary Statistics

	2006	2009	2013	2016
Ethiopia				
Male-headed household	0.79	0.78	0.72	0.73
	(0.41)	(0.41)	(0.45)	(0.44)
Household head's age	42.91	45.76	47.34	48.34
	(11.45)	(11.43)	(11.91)	(12.75)
Household head's years of schooling	3.57	3.80	4.96	5.48
	(3.78)	(3.81)	(3.79)	(3.98)
Rural	0.65	0.64	0.61	0.60
	(0.48)	(0.48)	(0.49)	(0.49)
PSNP	0.28	0.28	0.20	0.14
	(0.45)	(0.45)	(0.40)	(0.35)
Consumption*	142.09	148.58	169.61	187.99
	(110.20)	(109.65)	(214.77)	(284.41)
Wealth index	0.29	0.34	0.38	0.41
	(0.18)	(0.17)	(0.18)	(0.17)
Peru				
Male-headed household	0.87	0.85	0.81	0.79
	(0.34)	(0.36)	(0.39)	(0.41)
Household head's age	39.82	41.62	43.44	44.77
	(11.27)	(10.95)	(11.23)	(11.57)
Household head's years of schooling	7.76	7.91	8.35	8.92
	(4.28)	(4.26)	(4.23)	(4.25)
Rural	0.29	0.27	0.24	0.22
	(0.45)	(0.44)	(0.43)	(0.42)
Juntos	0.16	0.16	0.19	0.19
	(0.37)	(0.37)	(0.39)	(0.39)
Consumption*	190.79	213.04	299.83	306.43
	(187.64)	(181.12)	(307.75)	(790.93)
Wealth index	0.48	0.55	0.60	0.64
	(0.23)	(0.20)	(0.19)	(0.17)
India				
Male-headed household	0.93	0.93	0.87	0.86
	(0.26)	(0.26)	(0.34)	(0.35)
Household head's age	39.86	40.46	42.79	44.67
	(11.31)	(9.39)	(8.88)	(9.17)
Household head's years of schooling	4.28	5.00	5.12	5.48
	(4.57)	(4.67)	(4.71)	(4.86)
Rural	0.75	0.75	0.71	0.70
	(0.43)	(0.43)	(0.45)	(0.46)
NREGA	0.65	0.65	0.65	0.65
	(0.48)	(0.48)	(0.48)	(0.48)
Consumption*	850.42	920.88	1069.34	1252.86
	(616.64)	(761.32)	(885.01)	(1133.96)
Wealth index	0.46	0.52	0.59	0.64
	(0.20)	(0.18)	(0.16)	(0.15)

Notes: These figures are means, with standard deviations in parentheses. $N = 10307$ in Peru, 11198 in Ethiopia, and 11555 in India.
* Total monthly expenditure per adult, in 2006 local currency.

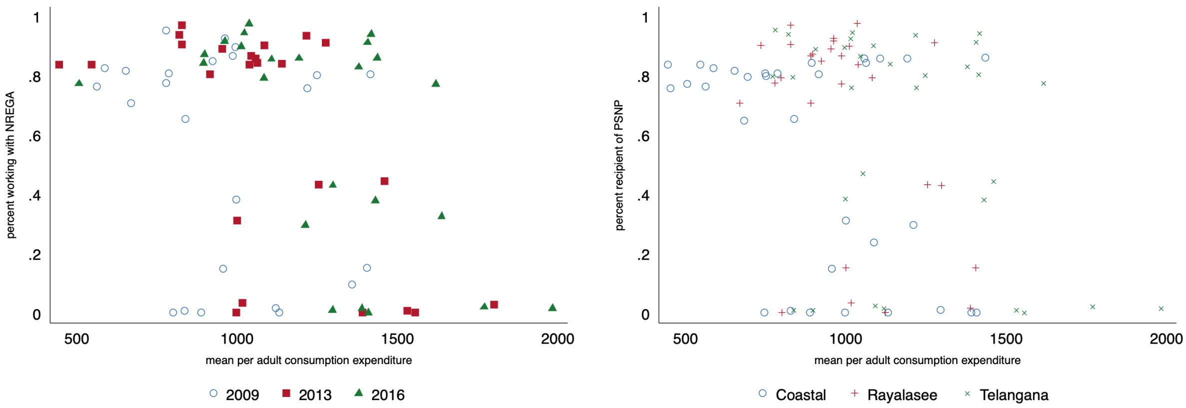
enjoys much-higher coverage while the SNNP region is only sparsely covered. In Peru, coverage is highest in the highland region, followed by the jungle. Coverage is sporadic in the coastal region. There is not much regional variation in NREGA coverage in India. We restrict the sample to early-phase districts, as NREGA was targeted at backward districts in the initial phases of the program.

Figure 3: Correlation between *Juntos* coverage and consumption



(a) Coverage by survey year **(b) Coverage by region**

Figure 4: Correlation between NREGA coverage and consumption

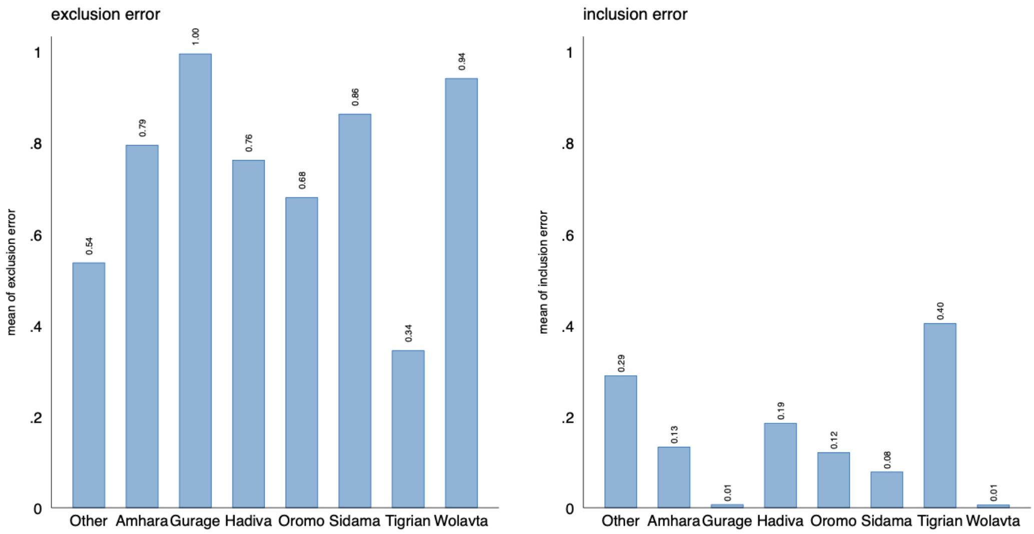


(a) Coverage by survey year **(b) Coverage by region**

We also carry out a back of the envelope calculation of targeting errors for the three programs. We define exclusion error as households in the bottom third of the consumption per capita distribution which do not benefit from (are enrolled in) a program. Similarly, we define inclusion error as households in the top two-thirds of the consumption distribution which benefit from a program. The exclusion error rate is given by the percentage of the bottom tercile not enrolled in the program, and the inclusion error rate is the percentage of the top two terciles enrolled in the program.

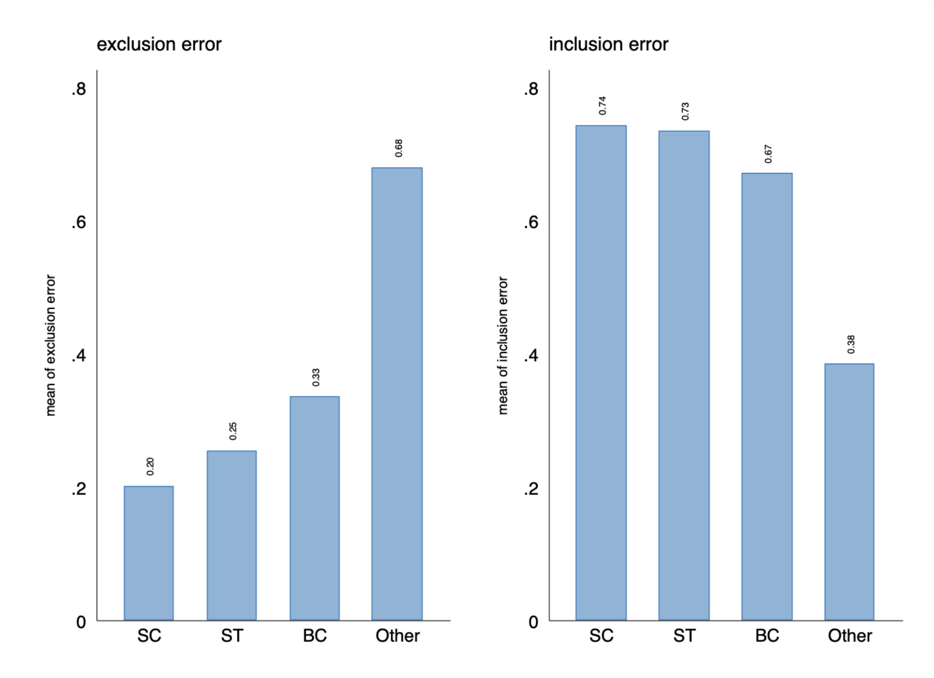
Figures 5 – 7 plot these errors by ethnicity. The exclusion rate is high in most of the ethnic groups in Ethiopia, as is to be expected given that most of our sample households are poor. Similar to the coverage rate, depicted in Figure 2, Tigrians have the lowest exclusion and the highest inclusion errors, while the three largest ethnic groups from the SNNP (Guraghe, Wolayta and Sidama) have the highest exclusion- and the lowest inclusion-error figures. The coverage rate in India is favorable to scheduled castes and scheduled tribes (Figure 6). The inclusion error rate is very low in Peru for all ethnic groups (Figure 7).

Figure 5: PSNP exclusion and inclusion errors, by region



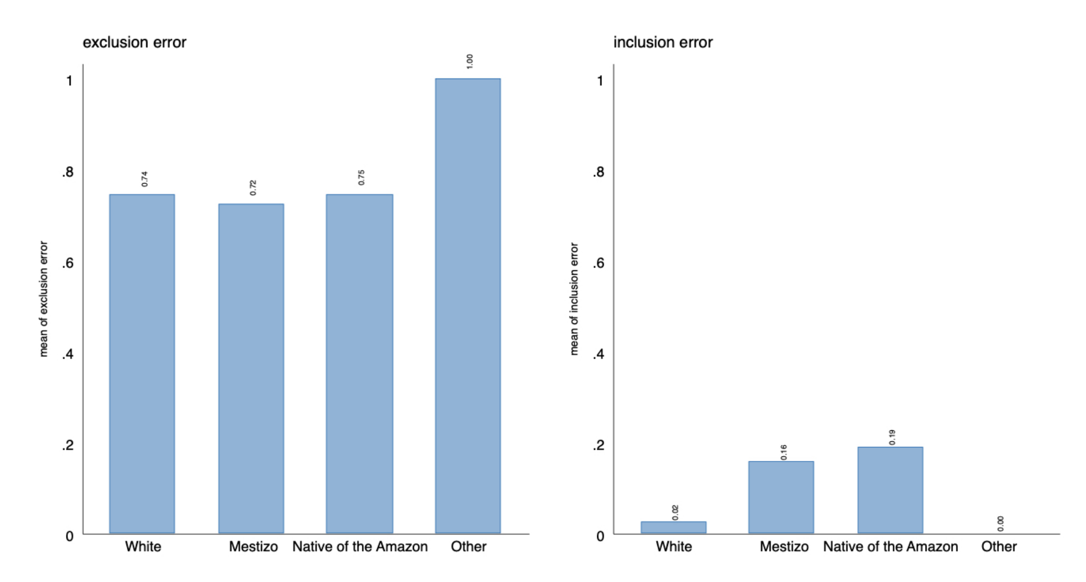
Left panel: percentage of the lower tercile that is not enrolled in PSNP. Right panel: percentage of the top two terciles enrolled in PSNP.

Figure 6: NREGA exclusion and inclusion errors, by ethnicity



Left panel: percentage of the lower tercile that is not enrolled in NREGA. Right panel: percentage of the top two terciles enrolled in NREGA. The sample is restricted to early-implementing districts.

Figure 7: *Juntos* exclusion and inclusion errors, by ethnicity



Left panel: percentage of the lower tercile that is not enrolled in *Juntos*. Right panel: the percentage of the top two terciles enrolled in *Juntos*.

3. Methods

3.1. Consumption Inequality

The outcome variable that we consider in this paper is household consumption expenditure. Inequality is typically thought of with respect to income, as income provides a relatively-clear indication of the ability of an individual to meet their material needs in the short term (McGregor et al., 2019).

In a developing-country context, such as the three countries we consider here, consumption data are widely-used to estimate both poverty and inequality (Ravallion, 1995; Chen and Ravallion, 2010). One reason is that data on income is not readily available. Given the relatively large informal sector in developing countries, it is difficult to collect income information from self-employment and subsistence farming. Individuals are often paid in kind for the services they provide, and receive transfers from friends and governments. This measurement error leads to underestimation of the mean income among the poor, and in this setting consumption is a more-direct measure of individual well-being. Consumption is also a relatively stable measure, particularly compared to income, as households smooth consumption over their lifetime.

Consumption may nonetheless be harder to measure accurately than income. In addition, measurement error is a major concern in using household surveys to provide consumption data. For instance, it is often difficult to impute a monetary value to goods and services that are consumed from own production. However, in the Young Lives dataset, data on the value of these consumed food items (in the current local currency) were collected. The consumption expenditure aggregate is made up of the total value of food items purchased and consumed, food items from home production (from own harvest or from stock), and food items received as gifts or transfers. In all three countries and in each round, the aggregate consumption expenditures are adjusted by the current household size (i.e. all members that live in the household as reported in the household roster, including children), and therefore are expressed in per capita terms.[5]

3.2. Dimensions of Analysis

One of the fundamental questions of empirical inequality analysis is inequality amongst whom. The choice of the group, as well as the individual, unit of analysis is an important first step in understanding the status and dynamics of horizontal inequality (HI) in a country. Stewart (2008) recommends considering alternative group classifications (for example, ethnic, regional, and religious), to form the relevant identity groups: the group boundaries that individuals care about, and the boundaries on the basis of which discrimination or favouritism occurs (Stewart, 2008).

[5] In Ethiopia the results are reported in 'per adult' terms, whereby real expenditure is divided by the current household size in each round adjusted for adult equivalence.

According to Stewart (2008), there are three conditions for categorizing individuals into groups. First, group membership is somewhat static: that is, members are not able to change groups easily. Second, group membership is recognized not only by the individuals themselves and their group, but also by other members of society. Last, group membership is meaningful to the individual, for example it is an important factor in their identity.

Our main focus is on groups as defined by ethnicity (broadly defined, e.g. including caste in India) and religion. These group types are considered plausibly exogenous, and constitute a relevant subset of all of the potential circumstances available in the the data. On occasion, we also examine difference between region of residence.

Ethnicity is at the center of the political structure in Ethiopia under the country's ethnic federalism system. There are nine ethnically-based regional states and two self-governing administrations. The Young Lives survey is carried out in five of these regions (Addis Abeba, Amhara, Oromia, Tigray, and Southern Nations, Nationalities and Peoples (SNNP) regional states). According to the 2007 Ethiopian census,[6] among the largest ethnic groups in Ethiopia are Oromo (34.4%), Amhara (27%), Somali (6.2%), Tigre (6.1%), Sidama (4%), Gurage (2.5%), Welaita (2.3%), and Hadiya (1.7%). With the exception of the Somali people, the other ethnic groups are fairly-well represented in the Young Lives sample.

In India the caste system is still extremely important in various social, cultural and political spheres. Four major caste systems are represented in our data. Scheduled Castes (SCs) and Scheduled Tribes (STs) are traditionally disadvantaged communities. SCs are the lowest in the traditional caste structure. STs are the indigenous people, living in and dependent on forests. Although a good number of them are mainstreamed and live in the plains, a considerable proportion continues to live in isolated hilltops with little access to services. Backward Classes (BCs) are people belonging to a group of castes who are considered to be backward in view of the low level of the caste in the structure. The "Other Castes" category comprises mostly of "forward castes" who traditionally enjoy a more privileged socioeconomic status (Boo, 2009).

Peru is also a multi ethnic country. The main ethnic groups include Mestizos (mixed Amerindian and White 60.2%), Amerindian (indigenous or Native Peruvians 25.8%) and White (5.9%) (INEI, 2018). These major ethnic groups are fairly-well represented in our dataset. Three broader regional groupings are considered in the Young Lives data: the coastal region (*costa*), which is bounded by the Pacific Ocean, the highlands (*sierra*), which is located on the Andean Heights, and the jungle (*selva*), which is located in the Amazonian Jungle.

Table 2 summarizes the empirical definitions for each group type considered in the study and the percentage of households in each category. Most households are male-headed in all three countries (77%, 84% and 90% in Ethiopia, India, and Peru respectively). Over 71% of the sample in Ethiopia are Orthodox Christian, while 87% are Hindu in India. Catholics make up 82% of respondents in Peru. Last, 63% and 73% of the sample reside in rural areas in Ethiopia and India, while only 27% do so in Peru.

[6] The latest census conducted at the time of writing.

Table 2: The Distribution of Group Composition in the Young Lives Sample (Percentages)

	Ethiopia		Peru		India	
Region	Tigray	20.18				
	Amhara	19.81	Costa	40.03	Coastal Andhra	35.03
	Oromia	20.58	Sierra	44.72	Rayalaseema	29.72
	SNNP*	24.7	Selva	15.25	Telangana	35.25
	Addis Ababa	14.73				
Ethnicity	Amhara	28.91				
	Oromo	20.54				
	Tigrian	22.06	White	5.31	SC*	19.28
	Gurage	8.01	Mestizo	91.87	ST*	13.32
	Sidama	5.44	Native	2.31	BC*	46.11
	Hadiya	5.06	Other	0.51	Other	21.30
	Wolavta	6.41				
	Other	3.57				
Religion	Orthodox	71.26	Catholic	81.67	Christian	4.87
	Muslim	16.07	Evangelist	13.34	Muslim	7.29
	Protestant	10.8	None	4.16	Buddhist	0.73
	Other	1.87	Other	0.83	Hindu	87.11
Place	Urban	36.84	Urban	73.3	Urban	26.94
	Rural	63.16	Rural	26.7	Rural	73.06
Gender	Male headed	77.07	Male headed	83.8	Male headed	90.05
	Female headed	22.93	Female headed	16.2	Female headed	9.95

* SNNP: Southern Nations, Nationalities and Peoples regional state; SC: scheduled caste, ST: scheduled tribes; BC: other backward classes.
The summary statistics is based on pooled data from all five survey waves.

3.3. Inequality Measures

One question of particular interest in the analysis of inequality is its evolution over time: this answers questions such as "Why did inequality decrease?" and "Who benefited the most from the change in the distribution of wealth?" Various measures of inequality have been introduced in the literature, which differ in their sensitivity to transfers in different parts of the distribution. Inequality measures should satisfy four basic properties: symmetry, population invariance, scale invariance, and the transfer principle (Foster et al., 2013).

The Gini coefficient is the most commonly-used inequality measure. This measures the average difference between pairs of incomes in a distribution, relative to the distribution's mean. Its values range from 0 to 1, indicating perfect equality and perfect inequality, respectively. The Gini coefficient satisfies all invariance properties, and the transfer principle. However, the Gini coefficient is neither transfer-sensitive nor subgroup-consistent.

Inequality may stem from different groups or sectors of population with different intensities. A critical feature of inequality measures is therefore their decomposability, such that the contribution of each group to total inequality can be identified. An inequality indicator is said to display the property of additive decomposability, defined by Shorrocks (1982), if it can be decomposed by population sub-groups and expressed as a weighted sum of a within-group and a between-group component.

One inequality measure that is additively decomposable and satisfies the subgroup consistency property is the entropy class of inequality measures. Generalized Entropy (GE) measures constitute the only family of indicators (up to a transformation) that display additive decomposability as well as anonymity, the population principle, the principle of transfers, and scale invariance.[7] The GE measures depend on a parameter α that expresses the sensitivity of the indicator to trensfers in different parts of the distribution. The special cases of $\alpha = 1$ and $\alpha = 0$ are known as the *Theil index* and *Mean Log Deviation*, respectively.

3.4. Oaxaca-Blinder decompositions of consumption differentials

We first look at the evolution of consumption differentials over time in our three sample countries. We calculate the gaps in log per capita consumption between various groups, adjusted for covariates: gender, age and education of the household head, household size, place of residence (the State, as well as a dummy for rural residency). We in addition control for religion in the decompositions according to ethnicity, and vice-versa. The Oaxaca-Blinder method then decomposes the (adjusted) gaps in mean consumption between groups into a part that is due to differences in the mean values of covariates between groups (the "explained" part) and a part that is attributable to differences in returns to covariates (the "unexplained" part). This last part can be interpreted as a measure of discrimination; under the conditional-independence assumption, it is also equivalent to a causal effect of being a member of a given group on the dependent variable (Fortin et al., 2011; Słoczyński, 2015).

3.5. Decomposition of Inequality

Decomposing inequality by components can help to define adequate economic policies that aim to reduce inequality and poverty. We consider three related approaches of inequality decomposition. First, we use the GE class of inequality measures to decompose overall inequality into between- and within-group components. Second, we decompose the Gini coefficient into three components – between group, within group and an overlapping term – to analyse the role that groups play in total inequality. Finally, we follow Cowell and Fiorio (2011) and use regression-based decomposition analysis to show how individual characteristics help explain overall inequality.

Let Y_i represent the consumption expenditure of household $i \in \{1, \ldots, n\}$. $\bar{Y}$ is the sample average. Let X represent the complete population formed by n households that can be partitioned into K sub-groups of n_k households each, such that $X = \bigcup_{k=1}^{K} X_k$ and $n = \sum_{k=1}^{K} n_k$. $\bar{Y}_k$ is the sample average of sub-group X_k. The GE measures calculated over

[7] The Gini coefficient is not perfectly decomposable, as it has a non-zero residual K as well as *within* and *between* inequality. It is perfectly decomposable only when the rankings by subgroup incomes do not overlap, i.e. the relative position of each individual in the subgroup income distribution is the same as in the total income distribution. The residual K is positive, instead, when ranking by subgroup incomes that overlap (Bellù and Liberati, 2006).

the entire population, $GE_\alpha(X)$, can be expressed as:

$$GE_\alpha(X) = \underbrace{\sum_{k=1}^{K} \frac{n_k}{n} \left(\frac{\bar{Y}_k}{\bar{Y}}\right)^\alpha GE_\alpha(X_k)}_{within} + \underbrace{GE_\alpha\left(\bigcup_{k=1}^{K} X_k\right)}_{between}$$

where $GE_\alpha(X_k)$ is the value of the GE indicator calculated for the households belonging to sub-group X_k:

$$GE_\alpha(X_k) = \frac{1}{\alpha(\alpha-1)} \frac{1}{n_k} \sum_{i=1}^{n_k} \left(\left(\frac{Y_i}{\bar{Y}_k}\right)^\alpha - 1\right)$$

and $GE_\alpha\left(\bigcup_{k=1}^{K} X_k\right)$ is the between-group component, given by:

$$GE_\alpha\left(\bigcup_{k=1}^{K} X_k\right) = \frac{1}{\alpha(\alpha-1)} \sum_{k=1}^{K} \frac{n_k}{n} \left(\left(\frac{\bar{Y}_k}{\bar{Y}}\right)^\alpha - 1\right)$$

The within component is calculated as the weighted sum of the value of the indicator in each of the K sub-groups. The between-group component is calculated as the value of the indicator of a distribution with K elements, each having as consumption expenditure the mean of consumption in the corresponding group and as weight the population share of the corresponding group.

Unlike the GE measures, the Gini coefficient cannot, in general, be decomposed by population sub-groups as a sum of a within and a between component. However, a decomposition into two components, within and between, is possible when the population is partitioned into "non-overlapping" groups. The decomposition proposed by Dagum (1997) sets out the Gini as a sum of three factors: $G = G_w + G_{nb} + G_t$. Here G_w is the within component, G_{nb} the net contribution of the extended Gini inequality between sub-populations, and G_t the contribution of the income intensity of transvariation between sub-populations. Dagum (1997) gives a socio-economic interpretation to each of these three factors in terms of their contributions to total inequality. The term G_t is equal to zero in the case of non-overlapping population sub-groups. The G_w component allows us to evaluate how the consumption variability within the sub-group populations influences total inequality, while the contribution attributable to the differences between the subgroups is given by G_{nb} and G_t. The meaning of G_t is not so straightforward, but it is useful to point out a considerable degree of overlapping indicates a small contribution of subgroups to total inequality, while low levels of overlapping suggest a larger contribution (Costa, 2019).

Cowell and Fiorio (2011) characterize a regression-based inequality decomposition using the decomposition rules of Fields (2003) and Shorrocks (1982). They begin by expressing household consumption expenditure as $Y = X\beta + \varepsilon$, where X is the $(n \times M)$ matrix of individual and household characteristics (such as age, education, household size, urban/rural location, etc.), β is a $(M \times 1)$ vector of coefficients and ε is an $(n \times 1)$ vector of residuals. A sample of observations $\{(y_i, \mathbf{x_i}) = (y_i, x_{1i}, \ldots, x_{mi}), i = 1, 2, \ldots n\}$ can then be used to estimate the model. Using this expression, per-capita consumption expenditure of household i is then represented as:

$$y_i = \sum_{m=1}^{M} \hat{\beta}_m x_i^m + \hat{\varepsilon}_i$$

where $\hat{\beta}_m$ is the Ordinary Least Squared (OLS) coefficient estimate, $\hat{\varepsilon}$ is the OLS residual for household i, and $m = 1, 2, \ldots, M$ are household-level characteristics. Shorrocks (1982) suggests that inequality measures can be written as a weighted sum of incomes, such that,

$$I(Y) = \sum_{i=1}^{n} a_i(Y) y_i$$

, where a_i are the weights, y_i the consumption of household i, and Y the vector of household-consumption expenditures. Hence, by analogy, the shares attributable to the characteristic $m = 1, \ldots, M$ take the form:

$$s_m = \hat{\beta}_m \left(\frac{\sum_{i=1}^{n} a_i(Y) x_i^m}{I(Y)} \right)$$

This decomposition might be applied to any inequality index that can be written as a weighted sum of incomes.

By applying a regression-based factor-source decomposition, Cowell and Fiorio (2011) show that the contribution of each right-hand-side variable to inequality can assessed. Their factor-source decomposition of within-group inequality also shows whether one variable contributes uniformly to inequality in each subgroup or has a disproportionate effect across the subgroups.[8]

[8] Cowell and Fiorio (2011) warn that this is not a structural econometric approach, and its specification may not be suitable for a causal interpretation.

4. Results

4.1. Patterns of and trends in horizontal inequality

To visually examine the actual group-specific consumption distributions in our three countries, Figure 8 presents density plots that are non-parametrically estimated via an adaptive kernel. For clarity of illustration, the consumption figures are truncated at value of 1000 ETB in Ethiopia, 4000 INR in India and 1000 PEN in Peru.[9] There is clear regional variation in Ethiopia and ethnic disparities in India and Peru.[10] The groups differ in their average consumption, with the distribution of consumption expenditure of households in lower-caste groups in India and natives in Peru being located more to the left of the distribution. For all groups in the three countries, there has been a slight rightward shift in the shape of the distribution over time.

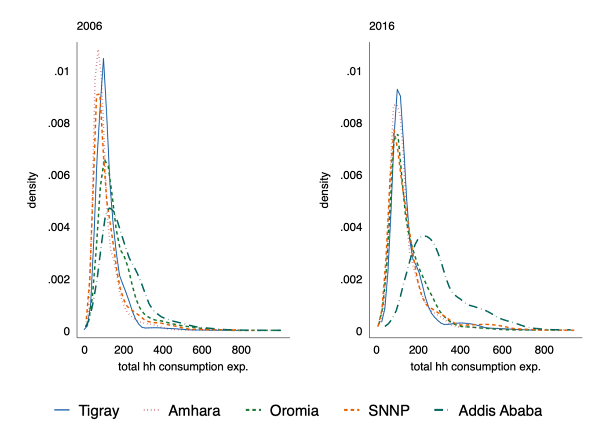
Figures A.2 – A.4 in Appendix A present a more detailed description of inequality trends by year, the gender of the household head, and program-participation status. In India and Peru, we see a change in the shape of the distribution over time, with a shift of the density from the middle towards the right tail of the distribution. The distribution remains largely unchanged in Ethiopia. The consumption distributions of female- and male-headed households overlap, suggesting only a small difference in consumption expenditures between two household types. The distribution moves slightly to the right in the post-program period for program-participant female-headed households in Ethiopia.

We also observe a number of common patterns in inequality trends in all three countries. The distribution of consumption among program participants is skewed to the left relative to non-participants, and this pattern persists over the ten-year period. However, there is a clear rightward shift over time in the distribution of program participants in India and Peru, and a slight shift in Ethiopia, suggesting that the consumption expenditures of beneficiary households increased over time.

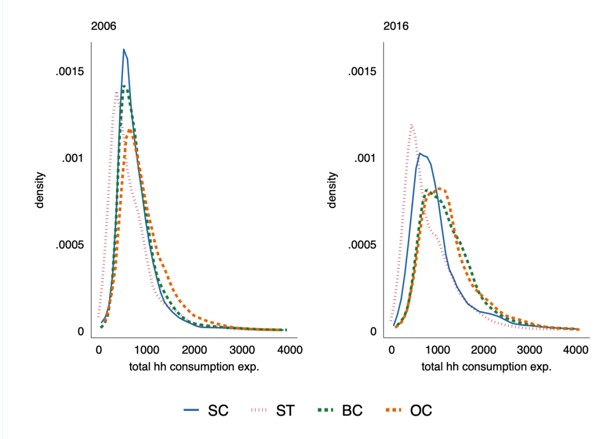
[9] ETB = Ethiopian birr; PEN = Peruvian soles, and INR = Indian rupees.

[10] As regional States are based on ethnicity in Ethiopia, for the sake of brevity we here present regional instead of ethnic trends.

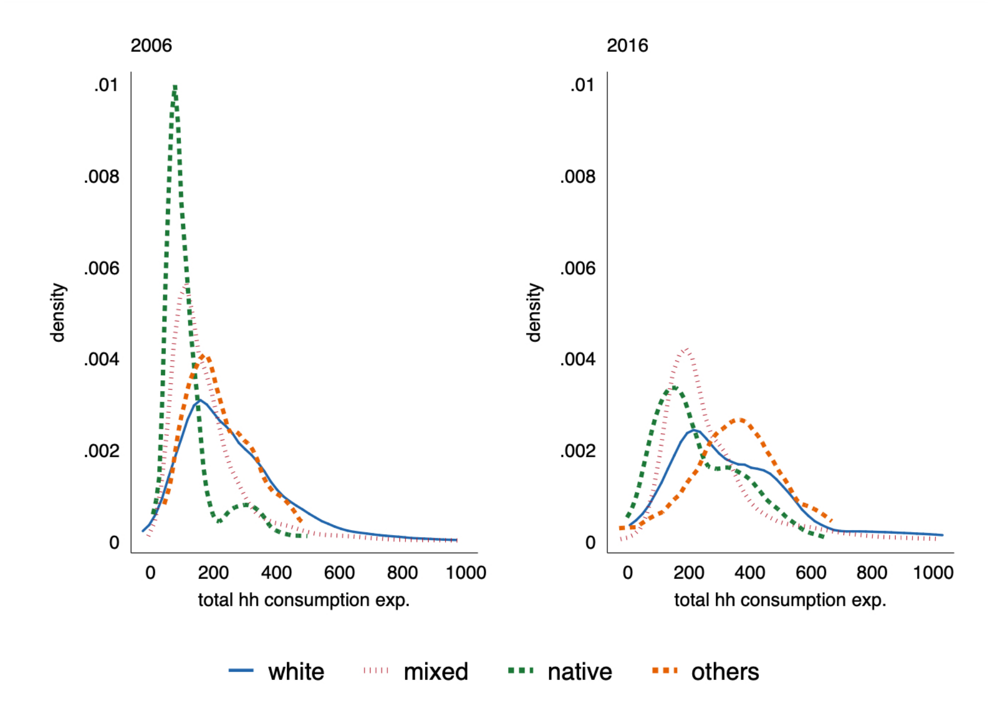
Figure 8: Consumption distribution by year and region/ethnicity



(a) Ethiopia



(b) India



(c) Peru

Left panel: percentage of lower tercile not enrolled in *Juntos*. Right panel: percentage of top 2 terciles enrolled in *Juntos*.

In addition to non-parametric kernel estimation, we also look at the change in inequality by plotting Lorenz curves over time. Figures A.5 - A.9 in Appendix A show these Lorenz curves for the three counties by year, ethnicity, gender, and program-participation status. There is no clear 'Lorenz dominance' between the male- and female-headed household distributions, as the two curves overlap at most points of the distributions in all the three countries. Similarly, the curves for different ethnic and regional groups overlap or cross over the years. However, we do see that the Lorenz curve for program participants always lies above that for non-participants in all three countries, implying less inequality among participants than non-participants.

We have calculated the overall inequality trend over the ten-year period using the different inequality measures discussed in Section 3.3. We consider the Gini coefficient and two GE inequality measures: GE(0), also known as Theil's L (and sometimes referred to as the mean log-deviation measure), and GE(1), Theil's T index. Figure 9 plots the results. Overall, consumption inequality rises slightly over time in Ethiopia and India and is largely stable in Peru. The results for the Gini and the two GE horizontal-inequality measures for all groups in Ethiopia are similar: inequality slightly fell between 2006 and 2009, followed by a rise in 2013 and 2016.

Figure 9: Consumption inequality trends

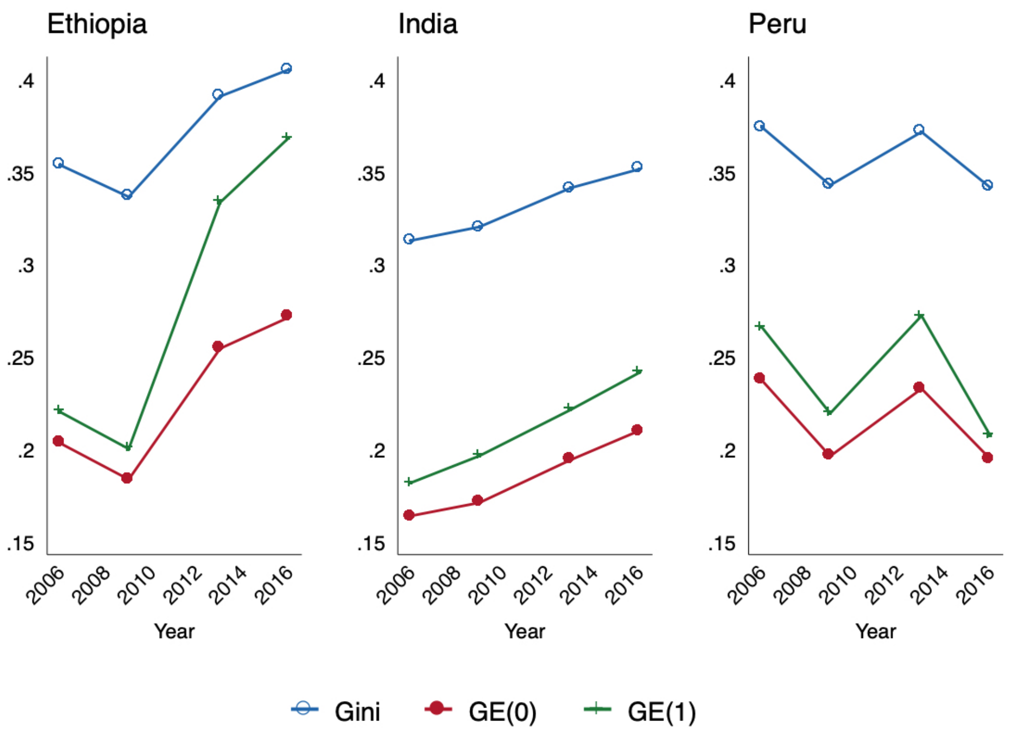


Table 3 shows the results disaggregated by program status. Similar patterns are apparent in all three samples. On average, program-participant households have lower initial inequality levels. In Ethiopia and Peru, the PSNP and *Juntos* beneficiaries experienced a fall in inequality, particularly between 2006 and 2009, and 2013 and 2016. Inequality increased for non-participants.

Table 3: Consumption inequality trends by program status

	Non-participants			Participants		
	Gini	GE(0)	GE(1)	Gini	GE(0)	GE(1)
Ethiopia						
2006	0.362	0.215	0.226	0.265	0.117	0.125
2009	0.343	0.192	0.204	0.244	0.098	0.102
2013	0.399	0.267	0.347	0.259	0.108	0.114
2016	0.412	0.281	0.377	0.231	0.088	0.092
India						
2006	0.344	0.199	0.227	0.286	0.134	0.153
2009	0.331	0.180	0.189	0.305	0.155	0.189
2013	0.343	0.199	0.217	0.331	0.179	0.210
2016	0.376	0.244	0.288	0.335	0.187	0.215
Peru						
2006	0.365	0.227	0.256	0.289	0.144	0.163
2009	0.340	0.195	0.217	0.248	0.102	0.102
2013	0.373	0.235	0.274	0.287	0.141	0.148
2016	0.385	0.259	0.441	0.276	0.137	0.144

We next present the results for the three inequality measures for Ethiopia, India and Peru for selected (more-salient) groups (i.e., ethnicity, region and religion) in Tables 4, 5, and 6. As the class of GE inequality measures are additively sub-group decomposable, we present overall inequality as the sum of a between-group and within group component. Between-group inequality is that calculated on the total population when each consumption level in a group is replaced by the mean of consumption in that group. This therefore reflects the mean differences across the groups. Within-group inequality is a weighted sum of the inequality measures calculated for each of the groups; this reflects the inequality that exists 'over and above' the mean difference across groups (Kanbur, 2006).

Considering the decomposition of the two GE indices, the within-group variation in general contributes substantially to total inequality in all three countries and for all of the waves considered. In general, between-group variation contributes the least to the total variation. Lanjouw and Rao (2011) notes that part of the reason for this is that the inherent properties of standard inequality decomposition measures tend to be structured so as to understate between-group inequality. Between-group inequality falls slightly over time in Ethiopia and Peru in all subgroups but rises marginally in India.

The within-group inequality at the national level reveals important differences. In Ethiopia, Tigray region and Tigrians experience the lowest within-group inequality, while the three ethnic groups from the SNNP Regional State (Wolayta, Guraghe and Sidama) exhibit the highest within-group inequality. In terms of religion, Orthodox Christians have the lowest within-group inequality figure. In India, Scheduled Tribes, the Coastal region, and Buddhists experience higher levels of within-group inequalities. In Peru, the Mestizo ethnic group, the

Sierra (mountain) region, and “other” minority religion followers experience higher within-group inequality.

The consumption-expenditure distributions of the various groups differ in many aspects, but also exhibit substantial overlaps. We carried out a Gini-index decomposition that explicitly considers this overlap. The third and sixth columns of Tables 4 - 6 present the results of this decomposition. Similar to the results obtained with the GE decomposition, the Gini decomposition also shows that large proportions of the total inequality are attributable to within-group inequality. However, we find substantial overlaps for the ethnicity decomposition in Ethiopia, and India, and for the regional decompositions in all three countries.[11] Note that the overlap term is largest for the decomposition across ethnic groups in Ethiopia. Foster et al. (2013) postulate that one possible reason could be the number of groups: as the number of groups rises,so does the possibility of overlap.

[11] The overlap term exists when the income distributions of each subgroup overlap along the income range; this is equal to zero when there are no subgroup income-distribution overlaps.

Table 4: Horizontal inequality measures (consumption), Ethiopia

	2006			2016		
Ethnicity	**GE(0)**	**GE(1)**	**Gini**	**GE(0)**	**GE(1)**	**Gini**
Total	0.199	0.214	0.350	0.253	0.321	0.393
Within	97%	97%	30%	98%	99%	30%
Between	3%	3%	16%	2%	1%	10%
Overlap			54%			60%
Amhara	0.221	0.238	0.370	0.269	0.331	0.406
Oromo	0.161	0.168	0.316	0.214	0.236	0.361
Tigre	0.158	0.177	0.310	0.218	0.281	0.365
Guraghe	0.243	0.285	0.383	0.249	0.265	0.389
Sidama	0.206	0.264	0.351	0.185	0.209	0.336
Hadiya	0.171	0.184	0.327	0.169	0.208	0.321
Wolayta	0.297	0.323	0.428	0.671	1.143	0.612
Others	0.161	0.171	0.320	0.230	0.249	0.376
Region	**GE(0)**	**GE(1)**	**Gini**	**GE(0)**	**GE(1)**	**Gini**
Total	0.204	0.223	0.354	0.276	0.389	0.407
Within	90%	90%	21%	90%	92%	21%
Between	10%	10%	31%	10%	8%	30%
Overlap			48%			49%
Tigray	0.123	0.134	0.273	0.181	0.246	0.328
Amhara	0.184	0.212	0.337	0.179	0.220	0.330
Oromia	0.163	0.174	0.319	0.209	0.250	0.357
SNNP	0.244	0.280	0.387	0.388	0.642	0.477
Addis	0.160	0.165	0.312	0.151	0.168	0.305
Religion	**GE(0)**	**GE(1)**	**Gini**	**GE(0)**	**GE(1)**	**Gini**
Total	0.194	0.208	0.345	0.242	0.302	0.385
Within	100%	100%	87%	100%	100%	85%
Between	0%	0%	2%	0%	0%	2%
Overlap			12%			13%
Orthodox	0.192	0.205	0.343	0.234	0.284	0.379
Muslim	0.210	0.230	0.358	0.277	0.329	0.414
Protestant	0.243	0.274	0.388	0.484	0.870	0.526
Other	0.299	0.326	0.423	0.251	0.292	0.393

Table 5: Horizontal inequality measures (consumption), India

	2006			2016		
Ethnicity	**GE(0)**	**GE(1)**	**Gini**	**GE(0)**	**GE(1)**	**Gini**
Total	0.153	0.172	0.303	0.198	0.236	0.341
Within	97%	98%	49%	96%	97%	51%
Between	3%	2%	14%	4%	3%	13%
Overlap			38%			36%
SC	0.132	0.147	0.281	0.199	0.218	0.349
ST	0.223	0.224	0.365	0.263	0.294	0.396
BC	0.140	0.158	0.292	0.186	0.233	0.332
OC	0.172	0.203	0.322	0.169	0.196	0.319
Region	**GE(0)**	**GE(1)**	**Gini**	**GE(0)**	**GE(1)**	**Gini**
Total	0.164	0.181	0.312	0.212	0.243	0.352
Within	95%	96%	32%	94%	95%	34%
Between	5%	4%	20%	6%	5%	22%
Overlap			48%			44%
Coastal	0.199	0.227	0.344	0.244	0.288	0.376
Rayalaseema	0.163	0.190	0.316	0.172	0.200	0.323
Telangana	0.109	0.123	0.259	0.175	0.205	0.321
Religion	**GE(0)**	**GE(1)**	**Gini**	**GE(0)**	**GE(1)**	**Gini**
Total	0.163	0.180	0.312	0.206	0.229	0.348
Within	100%	100%	98%	100%	100%	98%
Between	0%	0%	0%	0%	0%	0%
Overlap			2%			2%
Christian	0.159	0.178	0.308	0.329	0.518	0.434
Muslim	0.111	0.115	0.257	0.179	0.221	0.323
Buddhist	0.534	0.542	0.542	0.150	0.170	0.306
Hindu	0.163	0.180	0.312	0.206	0.228	0.348

Table 6: Horizontal inequality measures (consumption), Peru

	2006			2016		
Ethnicity	**GE(0)**	**GE(1)**	**Gini**	**GE(0)**	**GE(1)**	**Gini**
Total	0.236	0.269	0.372	0.256	0.433	0.385
Within	100%	100%	99%	100%	100%	99%
Between	0%	0%	0%	0%	0%	0%
Overlap			1%			1%
White	0.199	0.180	0.334	0.188	0.177	0.331
Mestizo	0.236	0.269	0.372	0.256	0.434	0.385
Native	0.198	0.213	0.350	0.179	0.164	0.323
Other	0.105	0.102	0.255	0.167	0.117	0.248
Region	**GE(0)**	**GE(1)**	**Gini**	**GE(0)**	**GE(1)**	**Gini**
Total	0.246	0.278	0.381	0.258	0.444	0.386
Within	98%	98%	46%	99%	99%	45%
Between	2%	2%	15%	1%	1%	11%
Overlap			40%			44%
Costa	0.158	0.179	0.310	0.300	0.630	0.408
Sierra	0.297	0.352	0.419	0.210	0.221	0.361
Selva	0.207	0.220	0.353	0.215	0.217	0.355
Religion	**GE(0)**	**GE(1)**	**Gini**	**GE(0)**	**GE(1)**	**Gini**
Total	0.240	0.272	0.376	0.263	0.445	0.389
Within	100%	100%	95%	100%	100%	95%
Between	0%	0%	1%	0%	0%	1%
Overlap			4%			4%
Catholic	0.241	0.273	0.376	0.265	0.451	0.390
Evangelist	0.200	0.204	0.344	0.158	0.168	0.322
None	0.213	0.218	0.355	0.252	0.293	0.388
Other	0.294	0.360	0.424	0.068	0.056	0.177

In general, our results are consistent with previous work that has looked at these the three countries. Woldehanna and Araya (2019) evaluate poverty and inequality trends at the national and regional levels in Ethiopia during the 1995–2015 period using data from the nationally-representative Households, Income, and Consumption Expenditure Survey (HICE) conducted by the Central Statistical Agency. They find that, despite the drop in all measures of national poverty (incidence, depth, and severity), inequality at the national level appeared to rise over time. The Gini coefficient inequality at the national level was about 0.29 in 1995, rising to 0.30 in 2010 and 0.33 in 2015, indicating a relatively smaller shift of economic gains from higher-income to lower-income households.

Similarly in India, Dang and Lanjouw (2018) find that the last three decades have seen an acceleration in the growth rate of national income, and a subsequent decline in poverty. However, evidence also shows that this growth has been accompanied by higher inequality, possibly in all dimensions. Measures of household inequality, such as the Gini coefficients of consumption expenditure, income, and assets across households, have also shown an increasing trend since 1991. They further show that local-level inequality (within-village, in rural areas; within-block in urban areas) accounts for the bulk of overall inequality in India.

Himanshu (2019) calculate the Gini index of income inequality in India from 2004/05 and 2011/12 using data from the nationally-representative India Human Development Surveys (IHDS). These figures were around 0.54 in both 2004/05 and 2011/12, with a marginal increase during this period. Using three quinquennial rounds of consumption expenditure data over two decades (1993–2012), Chauhan et al. (2016), estimate the extent of poverty and inequality in Indian regions, and find that the mean level of inequality measured by the Gini index rose from 0.30 to 0.36.

In Peru, official inequality figures published by Instituto Nacional de Estadistica e Informatica (INEI) show that, between 2007 and 2017, the Gini coefficient fell by 7 percentage points. A similar trend is corroborated by Herrera (2017) who finds that the levels of income inequality, measured with the Gini coefficient, are relatively high and show a slight downward trend between 2004 and 2015. The same trend is observed for real per capita expenditure inequality. The income Gini coefficients fluctuate between 0.51 and 0.44, and those relative to expenditure between 0.41 and 0.35. Castillo et al. (2020) finds that lower inequality was experienced in almost all political regions. When looking at the gains in equality between 2007 and 2017, the demographic boom (the fraction of adults in the households) and income growth (labor and private transfers) are the two most-important factors in explaining the drop in inequality.

4.2. Decomposition of consumption differentials between groups

4.2.1. Simple decompositions

Ethiopia The evolution of consumption differentials in Ethiopia with respect to ethnicity and religion is shown in Table 7. The gaps that are significant at the 5% level appear in bold (we do not comment on the decompositions of insignificant differences). Regarding ethnicity, in 2006, the gaps in (adjusted) consumption levels are significant at the 5% level for only three groups out of eight: the Oromo, the Guraghe and the Sidama. Note that for the Oromo, the average gap is negative (by -0.3 log birr), which means that this group has a higher consumption level than the overall population. For the Oromo, the negative gap is entirely linked to differences in mean characteristics, while for the two other groups (Guraghe and Sidama), the gap is predominantly due to the unexplained part, which accounts for respectively 97% and 66% of the gap in 2006.

The contrast between the left the right panels of the table shows the evolution of the gaps and their components between 2006 (Wave 2) and 2016 (Wave 5). The size of the Oromo advantage fell (-0.09 log Birr against -0.3 in 2006), again entirely explained by differences in characteristics. The size of the gap for the Guraghe changed sign, and became an advantage in 2016: -0.13 log Birr against 0.23 log Birr in 2006. The gap for the Sidama remained unchanged, with the same breakdown between the explained and unexplained parts. Finally, while there was no significant difference in consumption in 2006 between the Hadiya and the rest of the population, in 2006 the decomposition shows a significant gap of 0.27 log Birr, explained in equal part by differences in characteristics and returns to characteristics.

The bottom panel of the table shows the result of a similar decomposition of consumption gaps, but between groups defined by religion. The size of the gaps remain very stable over the 10-year interval under consideration: while the Orthodox have an advantage of around -0.10 log Birr, entirely accounted for by differences in characteristics, Muslims experience a shortfall in consumption of 0.13-0.15 log Birr. The gap for Protestants and other religious groups are generally not statistically significant. This overall stability might reflect the fact that religious affiliation and ethnicity are disjoint, in the sense that there is variation in religion within ethnic groups.

Overall, the evolution of consumption gaps between groups in Ethiopia is relatively stable, with the exceptions of the Gurage and the Hadiya.

Table 7: Ethiopia - Decomposition of consumption gaps

	2006			2016		
	Difference	Explained	Unexplained	Difference	Explained	Unexplained
ethnicity						
Amhara	0.05	0.18	-0.13	-0.06	-0.1	0.14
Oromo	**-0.3**	-0.32	0.02	**-0.09**	0.07	-0.08
Tigre	0.05	0.17	-0.13	0.04	-0.12	0.01
Guraghe	**0.23**	0.01	0.23	**-0.13**	-0.18	-0.03
Sidama	**0.26**	0.09	0.17	**0.23**	0.15	0.11
Hadiya	0.02	0.4	-0.38	**0.37**	0.16	0.11
Wolayta	0.07	-0.01	0.08	0.04	0.05	0.03
Others	-0.09	-0.25	0.16	-0.15	-0.01	-0.15
Religion						
Orthodox	**-0.11**	-0.12	0.01	**-0.10**	-0.11	0.01
Muslim	**0.13**	0.09	0.03	**0.15**	0.09	0.06
Protestant	0.07	0.13	-0.06	0.03	0.15	-0.12
Other	-0.08	-0.05	-0.03	-0.10	-0.15	0.05

India The consumption gaps between various castes and groups in India appear in Table 8, for 2006 (Wave 2) and 2016 (Wave 5). For Scheduled Castes (SC) and Scheduled tribes (ST), the gap widened over the years: from 0.05 log Rupees in 2006 to 0.18 log Rupees in 2016 for Scheduled Castes, and from 0.33 to 0.47 log Rupees for Scheduled tribes. For both groups, the unexplained component (due to returns to characteristics) increased over time, pointing towards increasing economic marginalization. In contrast, households belonging to the "other backward castes" (BC) experienced an advantage (a negative gap), and this gap seems to have grown over time and is mostly unexplained. Last, the "other castes" (OC) experienced a negative gap as well, which stays approximately constant over time, and with a similar-sized breakdown between the explained and unexplained parts.

The gaps with respect to religion appear in the bottom panel. The overall picture is of a great deal of stability in the consumption gaps between groups, as defined by their religion. The gap between Christians and the rest of the population widens somewhat (from 0.12 to 0.18 log Rupees), a change that is entirely attributable to differences in mean characteristics. The gap between Muslims and everyone else remained stable at -0.10 log Rupees.

Overall, there seems to be a growing gap between the living standards of the Scheduled

Tastes and Tribes on the one hand, and the Backward and Other Castes on the other hand. The question of whether the social safety net might have contributed to this trend or rather helped to counteract it will be examined in the next subsection.

Table 8: India - decomposition of consumption gaps

	2006			2016		
	Difference	Explained	Unexplained	Difference	Explained	Unexplained
caste						
SC	**0.05**	-0.03	0.08	**0.18**	0.01	0.17
ST	**0.33**	0.24	0.09	**0.47**	0.13	0.33
BC	-0.04	-0.01	-0.02	**-0.23**	-0.01	-0.22
OC	**-0.23**	-0.10	-0.13	**-0.19**	-0.11	-0.08
religion						
Christians	**0.12**	0.12	0.01	**0.18**	0.17	0.00
Muslims	**-0.10**	-0.26	0.16	-0.10	-0.26	0.17
Hindu	0.02	0.09	-0.07	0.00	0.08	-0.07

Peru The evolution of consumption gaps in Peru with respect to race is presented in Table 9, top panel. There are only three large groups in Peru: Mestizo (the majority group), Whites and Natives. At the baseline, Whites enjoyed a sizeable advantage of 0.37 log Soles per capita compared to the rest of the population. From 2006 to 2016, this gap fell to -0.23 log Soles; moreover, the unexplained part also fell, both in absolute value and in terms of the percentage of the gap. Conversely, the gap experienced by Natives also fell (from 0.40 log Soles in 2005 to 0.18 log Soles in 2016); this evolution is almost entirely accounted for by the difference in mean characteristics between this group and the others. Last, the gap experienced by Mestizos remained constant in the period under consideration (0.14-0.13 log Soles), and is mostly accounted for by differences in mean characteristics.

The evolution of consumption differentials according to religion, in the bottom panel, shows a similar evolution of narrowing gaps between groups. While Catholics enjoyed a negative gap in 2006 of 0.14 log Soles per capita, this gap fell to -0.06 log Soles ten years later. Similarly, the consumption gap for Evangelicals, of 0.17 log Soles per capita in 2006, fell to 0.08 log Soles per capita in 2016. Interestingly, for both groups (Catholics and Evangelicals), the unexplained part, which represented approximately half of the total gap in the baseline, had all but vanished ten years later: the remaining gap is entirely attributable to differences in observable characteristics. The other minority religious groups do not have any discernible gap in the baseline or follow-up waves. Note however that these small groups represent only a small proportion of our sample, producing rather imprecise estimates.

Overall, the three countries under consideration present quite different characteristics and changes in inter-group differences. In Ethiopia, the differences in living standards between various groups are stable, with some exceptions (the erosion of the Oromo advantage, the reversal of the gap for Guraghe, and the widening gap for Hadiya). In India, the picture is one of a convergence between "Backward castes" and "Other Castes", with Scheduled Castes and Tribes being increasingly marginalized. In both countries, the gaps between religious affiliations remained stable, presumably because the differences in religious affiliation run within castes and ethnicities. Finally, in Peru the gaps between races and religions appears to be narrowing over time, with a disappearance of the unexplained part. In the next subsection we examine the possible role of covariates, among which participation in social-protection programs, in these evolutions.

Table 9: Peru - decomposition of consumption gaps

	2006			2016		
	Difference	Explained	Unexplained	Difference	Explained	Unexplained
Ethnicity						
White	**-0.37**	-0.25	-0.12	**-0.23**	-0.17	-0.06
Mestizo	**0.14**	0.08	0.06	**0.13**	0.09	0.04
Native	**0.40**	0.33	0.07	0.18	0.19	0.00
religion						
Catholic	**-0.14**	-0.07	-0.07	-0.06	-0.06	0.00
Evangelicals	**0.17**	0.10	0.07	**0.08**	0.08	0.00
None	0.02	-0.02	0.04	-0.02	0.00	-0.02

4.2.2. Detailed decompositions and the role of social-safety nets

To assess whether the various social-protection programs put in place contributed to the reduction of consumption differentials between group, we carry out another decomposition for 2016, with and without a dummy variable for program participation. The results for Ethiopia appear in Table 10. We only present the results for social groups (ethnicity and religion), for which we above identified significant mean differences in consumption, controlling for household characteristics. For three out of the four ethnic groups for which there is a significant gap (the Oromo, Guraghe and Sidama), the contribution of differences in PSNP participation is negative and significant. However, for the Oromo and the Guraghe, controlling for differences in participation in the PNSP increased the negative gap for these two groups. For the Sidama, controlling for differences in PNSP participation reduced the gap, although the size of the contribution is modest (8% of the adjusted difference).

Table 10: Ethiopa - detailed decomposition of consumption gaps

	Ethnicity				Religion	
	(1) Oromo	(2) Guraghe	(3) Sidama	(4) Hadiya	(5) Orthodox	(6) Muslim
overall difference	-0.09**	-0.13**	0.23***	0.37***	-0.10***	0.15***
	(0.04)	(0.06)	(0.06)	(0.06)	(0.04)	(0.04)
unexplained	0.07	-0.18***	0.15**	0.16***	0.01	0.06
	(0.04)	(0.06)	(0.07)	(0.06)	(0.04)	(0.05)
explained						
SP program (PSNP)	-0.01**	-0.03***	-0.02***	0.00	0.02***	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
% explained by human capital	4.4	3.1	-6.3	2.1	-15.9	-3.9
% explained by geography	-71.6	90.2	-29.8	-10.6	-80.0	-26.6
% explained by social protection	10.1	23.9	-8.1	0.6	-16.1	-4.1

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

India's detailed decomposition, in Table 11, shows that differences in program participation did not contribute significantly to income gaps in 2016, whether the groups are based on religion or on caste.

Last, in the case of Peru, in Table 12, differing participation in the *Juntos* program did not help explain the consumption gaps between religious groups; however, program participation did contribute significantly to consumption gaps for Whites and Mestizos. However, the sign of the contribution points toward an increase in consumption differentials: the contribution is negative for Whites, who have a negative gap (an advantage), and positive for Mestizos, who have a positive gap. We think that there are two possible explanations here: one is that there is actual discrimination in the access to the safety net; the other, more likely, one is that the OLS regression is biased by selection into Juntos program.

Table 11: India - detailed decomposition for caste

	Caste				Religion
	(1) SC	(2) ST	(3) BC	(4) OC	(5) Christian
overall difference	0.18***	0.47***	-0.23***	-0.19***	0.18**
	(0.04)	(0.04)	(0.03)	(0.03)	(0.07)
explained	0.01	0.13***	-0.01	-0.11***	0.17***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)
unexplained	0.17***	0.33***	-0.22***	-0.08**	0.00
	(0.03)	(0.04)	(0.03)	(0.03)	(0.06)
explained SP program (NREGS)	0.01*	0.01	0.01*	-0.02	0.00
	(0.01)	(0.01)	(0.00)	(0.02)	(0.00)
% explained by human capital	6.4	9.0	-4.7	33.5	9.0
% explained by geography	-23.0	4.1	5.1	-7.9	29.2
% explained by social protection	5.5	2.6	-2.3	12.9	1.7

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Peru - detailed decomposition of consumption gaps

	Ethnicity		Religion
	(1) White	(2) Mestizo	(3) Evangelicals
overall difference	-0.23***	0.13**	0.08**
	(0.07)	(0.06)	(0.04)
explained SP program (Juntos)	-0.05***	0.03***	0.00
	(0.01)	(0.01)	(0.01)
% explained by human capital	56.0	67.5	52.3
% explained by geography	-13.2	-15.3	0.4
% explained by social protection	19.9	23.3	4.8

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3. Regression-based factor source decomposition

The large within-group inequality we observe emphasizes the role of other household characteristics. We turn to a regression-based approach following Cowell and Fiorio (2011). Here a regression-based factor-source decomposition is proposed to assess the contribution of household-level characteristics, building on Fields (2003) and Shorrocks (1982). We estimate separate regressions for each subgroup and wave. All countries and periods include family variables (number of adults, number of children under age 18, whether the family owns their dwelling and land), age (and age-squared) and the education level of the household head, and program-participation status as covariates.

The inequality-decomposition estimates are listed for ethnic and religion subgroups in Tables 13, 14, and 15 for Ethiopia, India and Peru respectively. For the sake of brevity, the results are presented omitting the OLS coefficient estimates and their significance. The factor-source decomposition of the inequality in each subgroup is shown in percentage terms. These percentages exhibit the proportional contributions of different household characteristics to total explained inequality. After controlling for a set of individual and family characteristics, the residual within each subgroup for all three countries still accounts for a proportion ranging from 50% to 90%, which means that a large part of inequality is not explained by the variables included. However, the results are useful in showing how the explained part of consumption inequality is attributable to the different explanatory variables.

There is still some variation in the relative contribution of household characteristics to inequality for different subgroups. In Ethiopia, household-head education, household size and rural location contribute the most towards inequality for both ethnic and religious inequalities. PSNP participation accounts for a small proportion of within-group inequality for most groups, except in the Tigre ethnic group where 18% of the explained inequality is due to PSNP. This is consistent with our finding in S2.3, where we found higher participation levels in the Tigrai region. PSNP participation also accounts for 13% and and 8% of explained inequality for the Oromo ethnic and the Orthodox religion subgroups.

Table 13: Regression-based decomposition of inequality: Ethiopia

	Ethnicity					Religion		
	Amhara	Oromo	Tigre	Guraghe	Sidama	Orthodox	Muslim	Protestant
Residual	76.21	81.85	77.34	66.61	57.27	79.24	72.96	91.67
PSNP	0.66	2.28	4.04	−0.03	0.52	1.61	1.10	0.16
Male head	−0.07	−0.15	−0.28	1.59	0.01	−0.13	−0.40	0.02
Head age	0.21	0.57	−1.21	−0.58	2.31	0.20	0.53	−0.50
Age squared	−0.11	−0.13	1.46	0.34	−2.06	−0.16	−0.18	0.59
Edu.: Primary	−0.81	−0.05	0.04	0.44	−0.39	−0.28	0.26	−0.10
Edu.: Secondary	3.06	2.09	1.20	7.26	0.93	2.46	2.11	1.46
Edu.: Tertiary	8.27	1.58	5.41	0.26	5.18	4.98	1.85	−0.01
Household size	2.10	2.22	4.77	5.40	4.79	2.78	4.17	0.59
Prop of children†	0.33	2.70	0.45	−0.39	0.09	0.76	0.45	0.89
Prop of old*	−0.03	0.01	−0.03	0.00	0.04	0.04	0.14	−0.01
Drinking water	0.30	0.24	1.15	4.17	1.19	0.18	1.71	0.61
Sanitation	0.81	0.63	0.99	−0.02	0.39	0.88	−0.08	0.10
Electricity	1.62	0.69	−0.44	7.13	4.34	0.97	2.62	0.66
Rural	6.49	6.05	5.12	−2.45	39.58	6.62	11.21	3.39
Own house	−0.56	0.69	0.66	12.03	−0.73	0.00	2.29	−0.15
Own land	−0.17	−0.83	−1.73	−14.43	−2.51	−0.80	−6.53	−0.25
Own livestock	1.71	−0.44	1.06	12.66	−10.95	0.62	5.80	0.86
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Note: Factor source decomposition of the within-group component of inequality of household consumption expenditure in Ethiopia using a decomposition by ethnicity and religion on pooled data. Estimation by each wave and for all subgroups is available on request from the authors.
† Proportion of household members age < 13; * Proportion of household members age > 60.

Similarly in India, the residual term accounts for a large proportion of within-group inequality. NREGA participation, however, is found to be an important contributor to within-group inequality in the Scheduled Tribes, accounting for about 45% of explained inequality. Again, this is in line with the analysis in Section 2.3, where Scheduled Tribes are found to have benefited from higher targeting. 13% of the explained inequality for the Hindu religious group is attributed to NREGA participation. Household demographics, such as the education of the head, the proportion of children and access to better sanitation, contribute towards the explained part of within-group inequality.

Table 14: Regression-based decomposition of inequality: India

	Caste[a]				Religion			
	SC	ST	BC	OC	Christian	Muslim	Buddhist	Hindu
Residual	87.19	74.14	90.33	85.24	95.15	83.31	51.07	85.80
NREGA	0.20	11.60	0.71	0.90	0.12	0.92	0.56	1.90
Male head	0.32	0.00	0.00	-0.01	0.17	0.00	0.28	0.00
Head age	0.32	0.47	1.47	0.81	1.91	5.31	-0.70	1.04
Age squared	-0.14	-0.17	-0.70	-0.23	-1.23	-3.13	-0.35	-0.48
Edu.: Primary	0.03	-0.14	-0.06	-0.59	0.12	-0.59	0.17	-0.15
Edu.: Secondary	1.52	1.61	0.98	0.80	-0.01	4.53	19.00	1.26
Edu.: Tertiary	1.25	4.72	0.82	6.52	0.04	1.78	0.03	2.95
Household size	1.55	0.35	1.40	2.36	0.53	4.59	0.39	1.25
Prop of children†	2.64	1.28	1.59	1.93	1.50	1.73	-0.08	1.89
Prop of old*	0.04	0.16	0.15	0.14	0.25	0.53	-0.13	0.03
Drinking water	0.01	1.39	-0.01	0.28	0.12	0.09	2.34	0.08
Sanitation	2.67	3.15	2.82	1.04	0.30	0.20	13.70	3.38
Electricity	0.04	0.60	0.41	0.10	0.17	0.09	5.33	0.43
Rural	2.10	0.28	-0.16	-0.03	0.02	-0.11	0.77	0.64
Own house	0.64	0.48	0.52	-0.03	0.00	-0.22	0.41	0.40
Own land	-0.22	0.18	-0.08	0.66	0.28	0.64	2.97	-0.14
Own livestock	-0.16	-0.10	-0.20	0.10	0.57	0.32	4.24	-0.30
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Note: Factor source decomposition of the within-group component of inequality of household consumption expenditure in India using a decomposition by caste and religion on pooled data. Estimation by each wave and for all subgroups is available on request from the authors.
† Proportion of household members age < 13; * Proportion of household members age > 60.
[a] SC, ST, BC, and OC are as defined in Table 2.

In Peru, we find that for all race and religious subgroups, household size and the proportion of children account for a large share of explained within-group inequality. Higher education also contributes to a larger share of inequality, except for Natives. Juntos participation represents 6% and 7% of explained inequality for the Mestizo and Catholic religious subgroups respectively.

Table 15: Regression-based decomposition of inequality: Peru

	Ethnicity			Religion		
	White	Mestizo	Natives	Catholic	Evangelist	None
Residual	72.18	83.44	48.67	78.98	74.65	81.27
Juntos	0.74	1.06	-0.36	1.43	0.64	0.37
Male head	0.57	0.00	0.53	-0.03	1.71	0.46
Head age	-0.01	0.83	7.35	0.27	5.42	0.85
Age squared	0.01	-0.44	-5.92	0.07	-3.98	-0.73
Edu.: Primary	-1.80	0.31	-5.66	0.80	-4.73	-1.39
Edu.: Secondary	-2.17	0.14	15.37	0.14	0.80	-0.43
Edu.: Tertiary	12.72	7.08	0.73	7.87	13.76	8.84
Household size	6.48	4.50	34.12	5.87	4.94	2.21
Prop of children†	5.84	1.57	2.29	2.26	5.03	0.31
Prop of old*	1.55	0.22	0.01	0.30	0.03	0.60
Drinking water	0.48	0.29	0.65	0.49	0.09	0.31
Sanitation	0.60	0.18	3.21	0.25	0.12	-0.02
Electricity	0.31	0.29	-1.16	0.33	0.31	0.05
Rural	0.87	-0.32	-0.67	0.14	0.01	-0.57
Own house	-0.35	0.23	-0.03	-0.05	-0.06	6.29
Own land	0.71	-0.26	1.36	-0.12	-0.13	1.54
Own livestock	1.25	0.87	-0.48	1.00	1.39	0.02
Total	100.00	100.00	100.00	100.00	100.00	100.00

Note: Factor source decomposition of the within-group component of inequality of household consumption expenditure in Peru using a decomposition by race and religion on pooled data. Estimation by each wave and for all subgroups is available on request from the authors.
† Proportion of household members age < 13; * Proportion of household members age > 60.

5. Discussion and policy implications

We underscore the role of the localized evaluation of inequality based on socially- and culturally-constructed boundaries. The results of our analysis above show that there are significant inequalities within and among different groups in the three countries we considered. Our decomposition analysis reveals that the contribution of within-group inequality to total inequality is much larger than that of between-group inequality in all the three countries and survey waves. These results are common in the related literature (see for instance McDoom et al., 2019; Dang, 2019). According to Kanbur (2006), regardless of the decomposition method used, the empirical contribution of the between-group component is rarely over 15%, and often under this figure. Hence, the smaller contribution of between-group inequality does not imply that redistribution in favor of disadvantaged groups is not important. The policy significance of this finding should be qualified by a closer examination of the patterns of inequality, the policy instruments at hand, their impacts, and their costs (Kanbur, 2006).

What is the role of social safety nets in the evolution of between-group inequality? The diversity of our results does not allow for generalizations. The easiest case is that of India, where NREGA participation does not appear to affect the between-group differences. The results on targeting, presented in Section 2.3, allow us to exclude the possibility that this is due to discrimination against Scheduled Castes and Tribes in access to the program: these two groups have higher inclusion and lower exclusion than other groups. The tentative conclusion is that NREGA, although effective in reducing poverty, might not be the right policy to counter the increasing marginalization of these groups. Policies explicitly targeting these groups appear to be warranted, especially given that the differentials in consumption are increasingly due to the "unexplained" part, which is usually interpreted as discrimination.

The biggest contribution in absolute value is found for the *Juntos* program in Peru, but goes in the wrong direction. This is not due to differential access to the program, as shown in Figure 6. We think that in this case this is possibly a statistical artifact due to selection bias in the program: the poorer an individual is, the more likely they are to be included in the program. Further research aiming at correcting this selection bias might shed light on the question.

In Ethiopia, differences in PSNP participation explain a relatively minor part of the total gap in consumption, but in some cases (Guraghe, Oromo) appears to exacerbate the differences. However, the targeting appears to be so restrictive (exclusion rates are generally around 80%) that it is difficult to reach a definitive conclusion: the restrictive character of this program might precisely be why its contribution to reducing inter-group differences appears so modest. On this ground alone, an expansion of the reach of the program might appear warranted, although our results caution against expecting an automatic reduction of between-group inequality from this expansion.

Conclusions

We have here described the role of three large-scale social-protection programs on horizontal inequality. We examine the changes in consumption inequality among culturally- and socially-defined groups in Ethiopia, India and Peru over the 2006-2016 period. We focus on two dimensions of horizontal inequality that capture the most-relevant aspects of between-group inequality: ethnicity and religion. These group types are considered plausibly exogenous, and constitute a relevant subset of all of the potential circumstances available in our data.

We document the change in between-group and within-group inequality among ethnic, religious, and regional groupings. We underline different evolutions in the three countries, with a modest reduction in between-group inequality in Ethiopia, a rise in India, and a drop in Peru. We find a strong correlation between living standards and social-protection program coverage in Ethiopia and Peru. The correlation is weaker in India. We also find that inequality among program participants is much lower than that for non-participants.

We use the GE class of inequality measures to decompose overall inequality into between- and within-group components. We find that within-group inequality accounts for the largest proportion of total inequality in all of the samples we considered. However, we are careful not to interpret this as calling for policy recommendations to reduce within-group inequality. Kanbur (2006) cautions that a higher normative premium is attached to between-group inequality. This is also evident in our sample, as program participation is highly correlated with reduced inequality for the disadvantaged group (for instance Scheduled Tribes in India).

The results from decompositions of consumption gaps between groups show that the social safety nets we analyzed did not lead to an automatic reduction in the mean differences between groups. In the case of India, factors other than the program are far more powerful in driving differences between groups, implying the need for dedicated policy initiatives in favor of marginalized communities. In other case, such as Ethiopia, the restrictive targeting of the program appears to be one limiting factor in a larger role in inequality reduction.

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A. Additional Figures

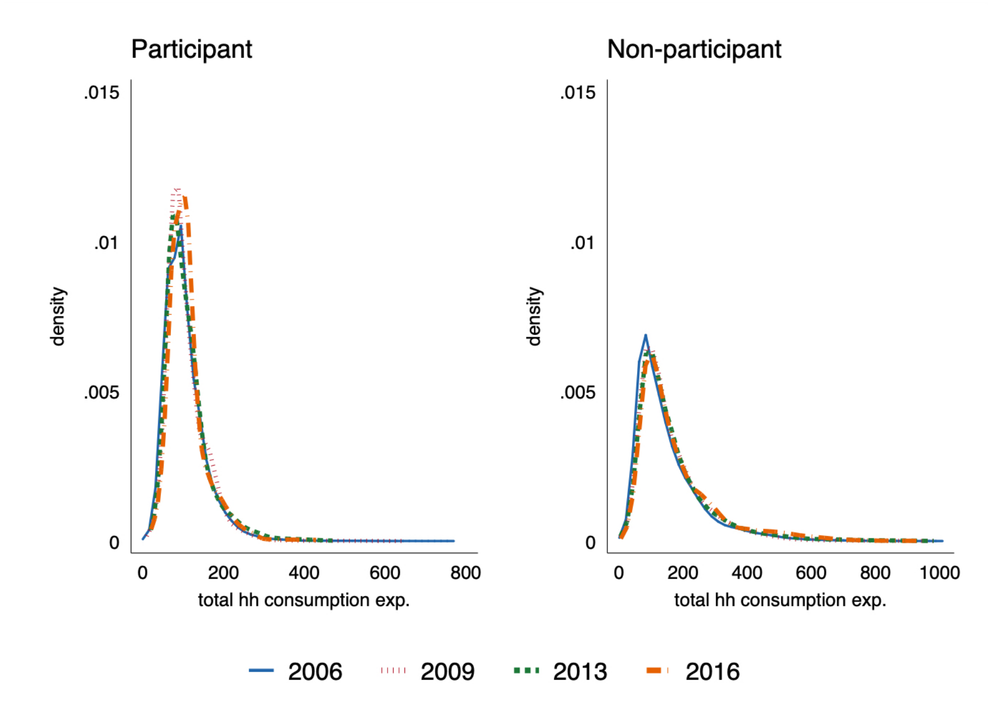


Figure A.1: Consumption distribution by year and program status: Ethiopia

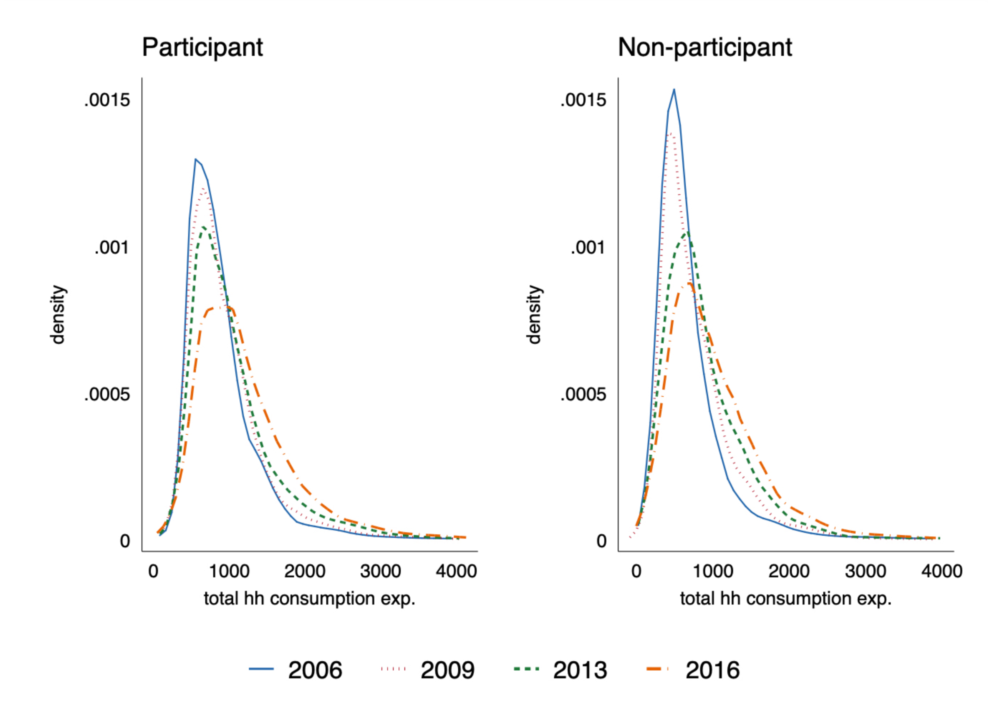


Figure A.2: Consumption distribution by year and program status: India

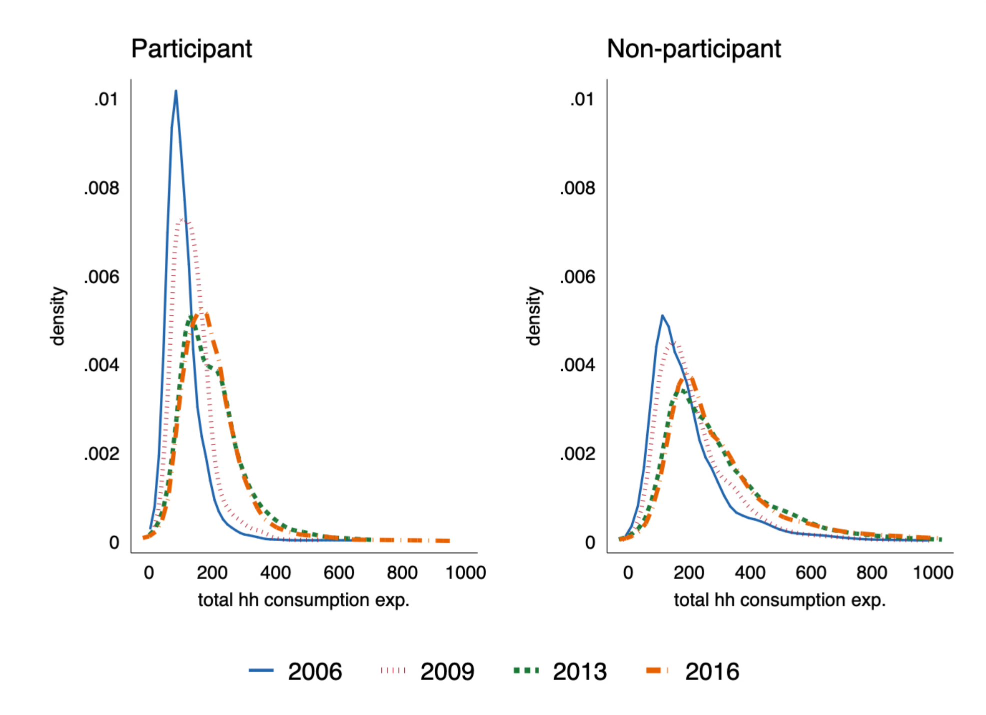
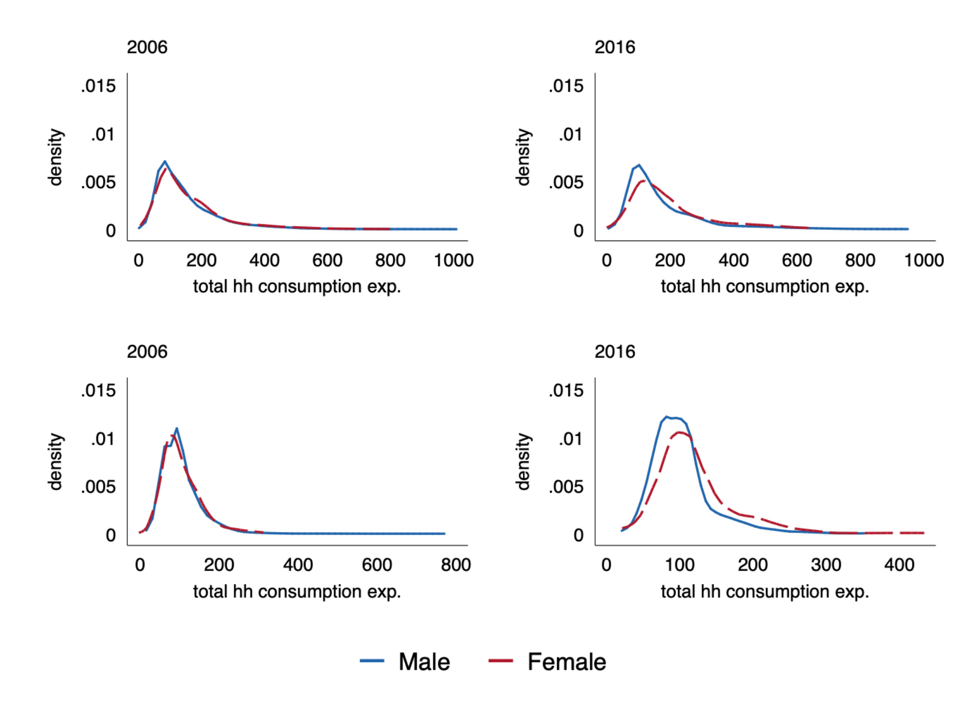
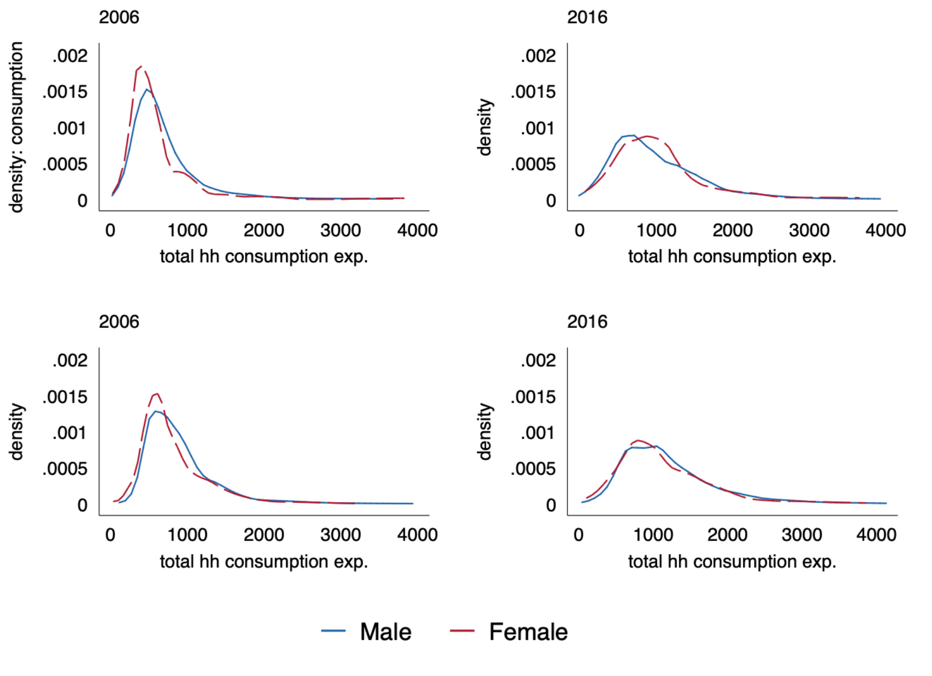


Figure A.3: Consumption distribution by year and program status: Peru



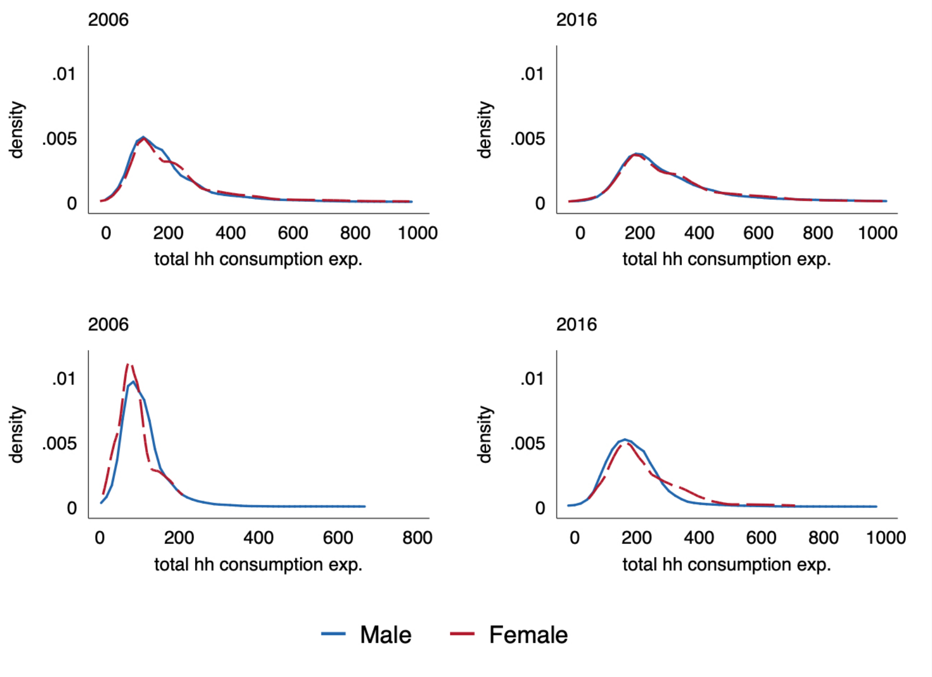
Note: Top panel: non-participants. Lower panel: participants

Figure A.4: Consumption distribution by year, gender and program status: Ethiopia



Note: Top panel: non-participants. Lower panel: participants

Figure A.5: Consumption distribution by year, gender and program status: India



Note: Top panel: non-participants. Lower panel: participants

Figure A.6: Consumption distribution by year, gender and program status: Peru

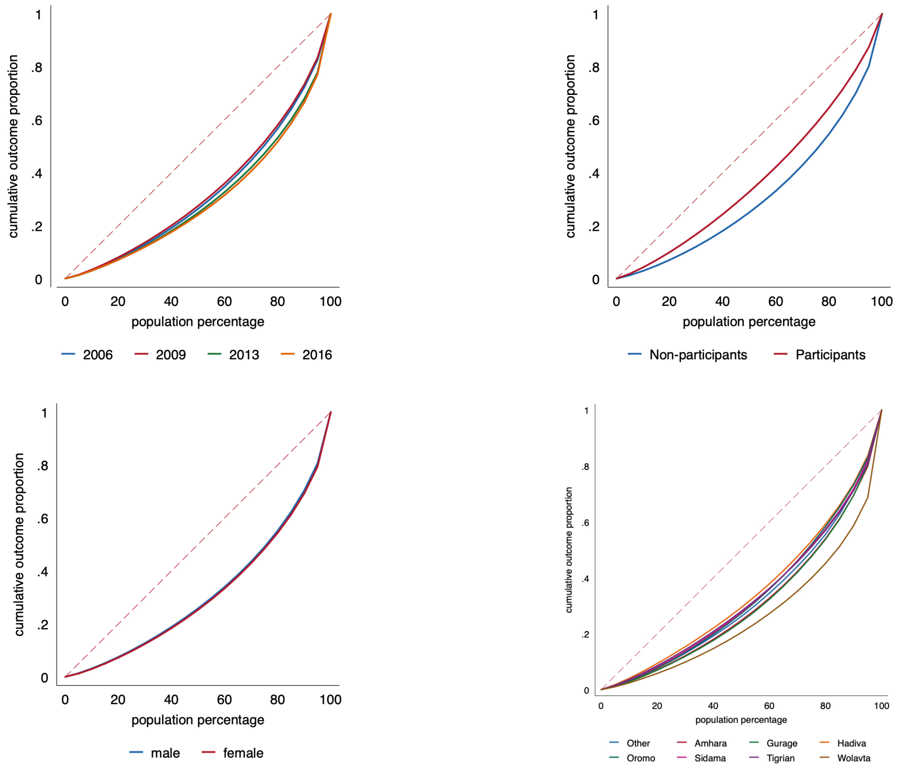


Figure A.7: Lorenz curves, Ethiopia (by year, program, gender and ethnicity)

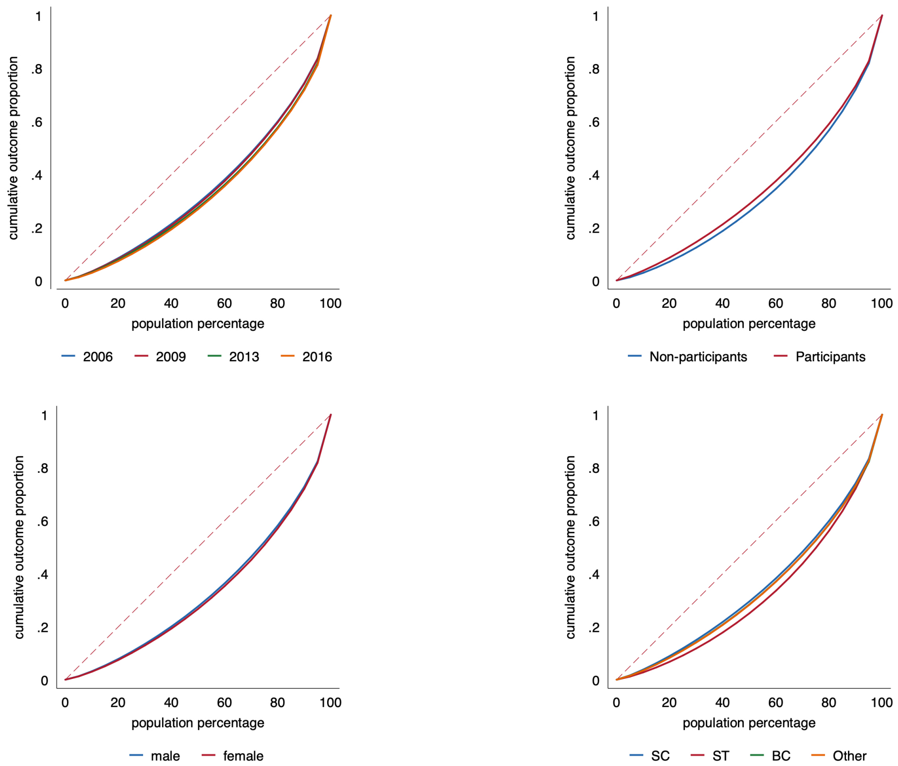


Figure A.8: Lorenz curves, India (by year, program, gender and ethnicity)

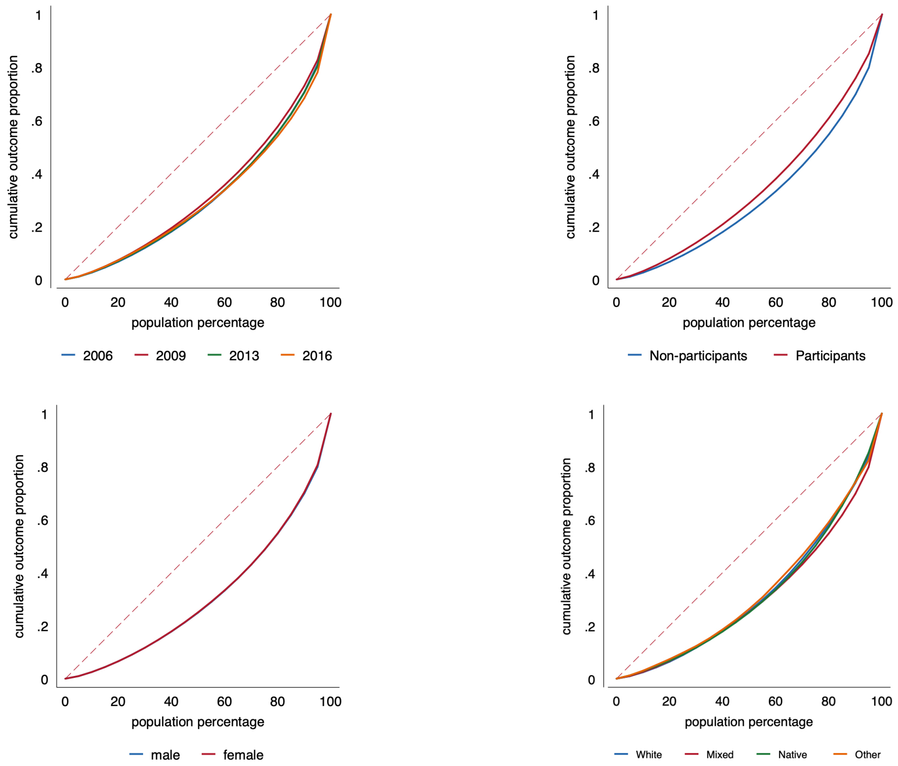


Figure A.9: Lorenz curves, Peru (by year, program, gender and ethnicity)

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