Who Should Be Served First? Multidimensional Prioritization in a Bolivian Cash Transfer Program

Abstract
Social protection programs in developing countries often rely on broad eligibility criteria that overlook the heterogeneity of beneficiaries' deprivation profiles. We propose an ex-ante microsimulation framework to evaluate the efficiency of conditional cash transfer (CCT) allocation rules in reducing multidimensional poverty. Applied to Bolivia's flagship CCT, Bono Juancito Pinto, using 2022 household survey data, we compare the current, uniform allocation rule against counterfactual prioritarian rules that concentrate resources first on households with the highest burden of overlapping deprivations. BJP has the explicit aim to reduce poverty in the long run, and we show that while it is generally effective, its impact can be considerably amplified under prioritarian rules. This efficiency is driven by a poverty reduction mechanism that resolves program targeted outcomes among the most deprived, and may pull some of these households out of multidimensional poverty. While our framework takes the program's eligibility criteria and associated exclusion errors as given, we demonstrate that a multidimensional lens for resource allocation can mitigate the fiscal inefficiencies of inclusion errors.

Keywords: Multidimensional poverty; Social protection; CCT allocation rules; Bolivia

1. Introduction

Bolivia has made significant progress in reducing income poverty over recent decades (Canavire-Bacarreza et al., 2025). Yet, more than a million Bolivians still live in multidimensional poverty, facing persistent, overlapping non-monetary deprivations on a daily basis (Alkire et al., 2022). The country's social protection system is primarily anchored in conditional cash transfer (CCT) programs, such as Bono Juancito Pinto (BJP), which has the primary objective of fostering human capital through education. These programs have significantly contributed to narrowing income gaps (Aguilar Pacajes, 2014; Canelas & Niño-Zarazúa, 2018). However, much less is known about how these programs relate to multidimensional poverty. While the Bolivian Constitution and national development plans explicitly align with the 2030 Agenda's commitment to eradicating poverty in all its forms, the country still lacks an official multidimensional poverty measure to inform the design, targeting, and evaluation of public interventions. This policy blind spot compromises the strategic allocation of resources by means of programs like BJP, which explicitly aim to reduce poverty in the long run[1], and raises questions about whether those most in need are effectively being reached (Atkinson, 2019; Alkire & Jahan, 2018).

In the specific case of the BJP, students under 21 years of age are eligible solely by enrollment in a public school, ignoring the heterogeneity of households' lived experiences (CEPAL, 2022). Moreover, resource allocation is uniform for all beneficiaries. This creates a targeting problem, as a child in a relatively stable household has the same policy priority as one suffering from, say, acute malnutrition and a lack of basic services. Without a multidimensional lens, the program is unable to prioritize those who are multiply deprived, monetarily or otherwise, and who potentially require more intensive interventions to ensure stable school attendance and long-term well-being.

[1] Supreme Decree No. 29246 (2007) establishes the Social Protection and Integral Community Development Policy, with the eradication of poverty as a central objective, to be pursued through strategies and programs—including the Bono Juancito Pinto—within the framework of the National Development Plan. Available at: https://www.planificacion.gob.bo/uploads/marco-legal/29246_ds.pdf

While several studies have described the state and evolution of multidimensional poverty in Bolivia (such as international estimates by OPHI and UNDP (2020) or subnational indices (Escobar et al., 2019, 2021), none of these measures have attained official status, nor have they been tailored to assess the performance of CCTs. Consequently, an analytical gap remains in understanding how flagship social protection programs interact with multidimensional deprivation. We argue that filling this gap is important because multidimensional measures offer a rigorous means of capturing overlapping deprivations that go beyond traditional income-based metrics (Alkire & Foster, 2011; Bourguignon & Chakravarty, 2003). By identifying individuals suffering from simultaneous deprivations, these frameworks can play a key role in policy targeting, specifically in identifying the most intensely deprived.

There are several methodologies available to construct such measures, including union and intersection approaches (Atkinson, 2003), indices focused on social exclusion (Chakravarty & D'Ambrosio, 2006), distribution-sensitive indices (Rippin, 2017), and dual counting approaches (Alkire & Foster, 2011). Among them, the Alkire-Foster (AF) method has emerged as the most widely adopted globally, providing a transparent compromise between axiomatic rigor, communicability, and the dimensional decomposability required for strategic resource allocation (Atkinson, 2019). Its institutional legitimacy is further underscored by the Commission on Global Poverty's recommendation to use counting approaches for monitoring multidimensional poverty (World Bank, 2016).

Against this background, we argue and empirically show that an AF-based Multidimensional Poverty Index (MPI) offers significant potential for refining CCT allocation rules. In our analysis, we conceptualize targeting as a two-stage framework consisting of an eligibility rule (who receives the benefit) and an allocation rule (how much do they get, or in what order; see Coady et al., 2004). In the case of the BJP, the eligibility rule is broad and determined by public school enrollment. We take this rule as given and focus on the efficiency gains of refining the allocation rule under a constant budget. By shifting from a myopic rule, where the program treats all eligible children identically akin to the current BJP payout, to prioritarian allocations, where resource delivery is guided by the intensity of overlapping deprivations, we assess how the program can better achieve vertical equity without necessarily restricting its universal scope within the public education system.

We argue that our results are not merely an artifact of the AF method but reflect the broader advantages of incorporating the joint distribution of deprivations in the form of a multidimensional measure into CCT design. Analysing these efficiency gains is particularly important for multifaceted interventions designed to influence several dimensions of well-being simultaneously (Suppa, 2025; Suppa et al., 2022). Unlike previous studies focused on mathematical budget optimization (e.g., Santos et al., 2023; Duclos et al., 2018), our approach prioritizes vertical equity by ensuring that the most acutely deprived receive resources first.

Our empirical analysis uses the latest wave of Bolivia's nationally representative Household Survey (2022) rather than administrative registries. This choice is driven by both data accessibility and the conceptual focus of the study. Rather than evaluating the current implementation of the BJP, we aim to simulate the ex-ante performance of counterfactual rules. For such forward-looking analysis, survey data are particularly appropriate as they allow us to construct a population-representative MPI and apply counterfactual rules across diverse subpopulations, an approach well-established in the literature on targeting design (Coady et al., 2004; Hanna & Olken, 2018). Furthermore, using publicly accessible survey data avoids the inherent biases of administrative registries, which are often incomplete, outdated, or limited to already-enrolled beneficiaries (Bound et al., 2001). At the same time, we ensure transparency and replicability in a context where official targeting mechanisms often lack consistent documentation.

Among our salient results, we find that allocating resources based on the extent of overlapping deprivations leads to significantly larger reductions in both the incidence and intensity of poverty. Specifically, our extreme prioritarian rule, which prioritizes those suffering from the highest number of simultaneous deprivations, outperforms all other rules across a range of plausible program impact scenarios.

The remainder of the paper is structured as follows. Section 2 reviews the conceptual and institutional landscape of social protection in Bolivia. Section 3 presents our methodological framework and MPI construction. Section 4 describes the data and our empirical strategy. Section 5 reports our main findings, highlighting the differential impacts of each targeting rule. Section 6 concludes by discussing policy implications and pathways for integrating multidimensional targeting into Bolivia's social protection architecture.

2. Brief Literature Overview

A social protection system comprises policies and programs designed to help individuals manage risk and alleviate poverty by promoting resilience, equity, and opportunity (Zhang et al., 2010). The World Bank (2012) emphasizes that these should function as a coherent portfolio with shared administrative subsystems, a perspective supported by Schnitzer (2018) and Beegle et al. (2018), who highlight the role of integrated systems and universal databases in improving coverage and reducing duplication. In Bolivia, however, the non-contributory pillar, which includes CCT programs like the Bono Juancito Pinto (BJP), often lacks this integration, leading to a blurred distinction between routine public investment and specific poverty interventions (Monterrey Arce, 2013). This institutional fragmentation likely contributes to suboptimal policymaking where the lack of a widely accepted and used multidimensional measure prevents the social protection system stakeholders from identifying overlapping deprivations among the population.

The tension between universalism and selectivity is central to our analysis. Historically, global shifts toward individual responsibility favored targeted over universal programs (Mkandawire, 2005), resulting in a Latin American hybrid model that combines universal systems with strict targeted transfers (Ocampo & Gomez, 2017). While universal approaches reduce stigmatization and avoid the social costs of penalizing honesty (Sen, 1992; Rothstein, 2001), they treat a potentially highly heterogeneous population as a single homogenous group. Conversely, traditional targeting, which consists of restricting benefits to those meeting specific criteria (Van Lancker & Van Mechelen, 2015) aims to maximize impact but often relies on infrequent data that produces significant inclusion and exclusion errors, leaving the poorest (or the most deprived) outside of the pool of beneficiaries (Hanna & Olken, 2018; Huang, 2021).

Addressing these inefficiencies requires adopting multidimensional targeting priorities. Duclos et al. (2018) demonstrate that when targeting is guided by the joint distribution of deprivations, either at the eligibility setting or allocation stages, multidimensional poverty falls more rapidly than under single-metric rules, largely because the treatment addresses the direct and indirect associations between dimensions. This prioritarian logic is further analysed by Santos et al. (2023), who use the simplest element in the the AF-based class of multidimensional measures (M_0) to guide fiscal policies. Their analyses suggest that prioritizing the worst off, meaning those suffering the highest intensity of deprivation, ensures vertical equity and optimizes poverty reduction across multiple dimensions simultaneously.

While alternative distribution-sensitive indices, such as those by Chakravarty & D'Ambrosio (2006), Datt (2019), and Rippin (2017) offer greater theoretical sensitivity to the concentration and correlation of deprivations, they often lack the full dimensional decomposability required for practical policy simulation. As noted by Suppa (2018) and Alkire et al. (2021), the AF framework allows for granular ex-ante simulations that can show exactly how specific program outcomes (such as school attendance) interact with other deprivation indicators. Consequently, we explore the usefulness of the AF method here as a functional instrument to refine the allocation rules of BJP, bridging the gap between axiomatic rigor and the practical necessity of fine-grained targeting (Hanna & Olken, 2018).

2.1. Bono Juancito Pinto (BJP): A flagship Bolivian CCT multifaceted program

Our analysis focuses on Bono Juancito Pinto (BJP), a CCT established in 2006 under Bolivia's Social Protection and Comprehensive Community Development Policy. The ultimate objective of BJP is to reduce poverty by lowering school dropout rates and incentivizing the matriculation and retention of students in the public education system. This is done by means of a cash transfer that offsets the direct and indirect costs of schooling. BJP grants two installments of BOB100 (around USD15) each, paid at the start and end of the school year to all the beneficiaries.

Since its inception, the program's scope has steadily broadened. In 2007, beneficiaries were children attending school up to sixth grade; in 2008 the beneficiary pool expanded to children attending second year of secondary education, in 2012 to the third year, in 2013 to the fourth year, and from 2014 onward, to the sixth and final year of secondary school (CEPAL, 2022). Eligible beneficiaries include students under 21 years of age enrolled in Community Vocational Primary Education or Community Productive Secondary Education at public and publicly-affiliated institutions in the Regular Education Subsystem. It also covers all learners, regardless of age or grade, attending public or affiliated Special Education Centers within the Alternative and Special Education Subsystem[2].

Expenditure on BJP has grown significantly over the last two decades, peaking at USD 69.61 million in 2021. From its inception in 2006, annual spending rose from USD 28.37 million to USD 68.64 million by 2022, maintaining stability despite a temporary surge during the COVID-19 pandemic (CEPAL, 2022). This financial expansion mirrors a substantial increase in program reach. Between 2006 and 2022, effective coverage more than doubled, growing from 1.08 million to 2.28 million beneficiaries. This growth was driven by both the broadening of eligibility criteria that we explained before and rising national school enrollment rates. Expressed as a share of the total population, coverage increased from 11.55% in 2006 to 19.05% in 2022, having reached a historic peak of 20.51% in 2015.

[2] Supreme Decree. 28899 (2006) establishes BJP. You can find the decree on https://siteal.iiep.unesco.org/sites/default/files/sit_accion_files/decreto_supremo_28.899-2006._bono_juancito_pinto.pdf

Table 1: Empirical evidence of the BJP's impact on several outcomes

Study	Data	Probability of school attendance			Probability of school enrollment					Probability of child labour				
			Area			Area		Sex			Area		Sex	
		National	Urban	Rural	National	Urban	Rural	Boys	Girls	National	Urban	Rural	Boys	Girls
Grigoli & Sbrana (2012)	MECOVI[3] 1997-2007	-0.006 (0.290)			0.072 (1.700)					0.035 (1.090)				
Vera Cossio & Contreras (2011)	EH 2005-2008	0.0386 (0.019)	0,218 (5) (0.068)	0,317 (6) (0.118)	0,0072 (1) (0.006)	-0,0193 (2) (0.017)	0,0472 (3) (0.015)			0.0004 (0.013)	-0,0076 (2) (0.007)	-0,129 (4) (0.050)		
Canelas & Niño-Zarazúa (2018)	MECOVI 2005-2013				0.052 (0.019)	-0.006 (0.022)	0.108 (0.046)	0.029 (0.026)	0.082 (0.029)	-0.062 (0.047)	-0.002 (0.043)	-0.097 (0.099)	-0.039 (0.066)	-0.078 0.065
Vera-Cossio (2022)	EH 2002-2009	-0.006 (0.016)			0.015 (0.015)					0.017 (0.019)				
AVERAGE PARAMETER		0.009	0.218	0.317	0.037	-0.013	0.078	0.029	0.082	-0.002	-0.005	-0.113	-0.039	-0.078

Notes: The values in parentheses represent standard errors and z-statistics in the case of Grigoli & Sbrana (2012).
(1) Effect of the variable pack, the aggregate effect of the BJP announcement. The effect of the BJP by cohorts—candidates for first, second, and third grade—is 2%*, 2.5%*, and 3%***, respectively, and the effect of the bonus is 5.11%***, but it shows selection bias.
(2) Effect of the variable pack for income quintile 3; all coefficients are non-significant.
(3) Effect of the variable pack for income quintile 2; the coefficient for quintile 4 is significant with a magnitude of 0.024*. For the rest of the quintiles, the effect is non-significant.
(4) Effect of the variable pack in quintile 2; the rest of the effects are non-significant.
(5) Effect of the variable pack for income quintile 5; the effects in quintiles 2 and 3 are significant with magnitudes of -0.11* and -0.147**, respectively.
(6) Effect of the variable pack for income quintile 5; the rest of the coefficients are non-significant.
The parameters linked to income quintiles will apply the most significant values to the eligible population, representing optimistic scenarios where the BJP benefits many people.
Source: Own elaboration based on Vega Cossio & Contreras (2011), Canelas & Niño-Zarazúa (2018), Grigoli & Sbrana (2012), and Vera Cossio & Contreras (2011).

Existing literature provides sound empirical evidence that BJP has yielded positive impacts on its intended outcomes, particularly regarding the probability of school attendance and enrollment. Because our study utilizes ex-ante simulation exercises to evaluate alternative allocation rules, the accuracy of our results depends on the calibration of realistic (conservative) impact parameters. To ground these simulations in empirical reality, we synthesize results from four rigorous evaluations, which are presented in Table 1 (Grigoli & Sbrana, 2012; Vera Cossio & Contreras, 2011; Canelas & Niño-Zarazúa, 2018; and Vera-Cossio, 2022). We specifically selected these studies because they provide the marginal effect estimates (the change in probability of an outcome) attributable to BJP, which are necessary to calibrate our counterfactual allocation rules. Other empirical studies, while valuable, were excluded from our calibration exercise because they solely rely on descriptive trends or relative changes that cannot be directly converted into the probabilistic impact parameters (in the causal sense) required for our microsimulation (e.g., Amarante & Brun, 2013; Marco Navarro, 2012; Tapia Huanaco et al., 2010; Yañez, 2012; Bauchet et al., 2018; Aguilar Pacajes, 2014).

A critical distinction in our calibration concerns the timing of documented impacts, specifically the difference between announcement effects and outcome effects. Regarding the announcement

[3] MECOVI is a regional program aimed at standardizing household surveys across Latin America and the Caribbean, funded by the World Bank, the Inter-American Development Bank, and the United Nations (Grigoli & Sbrana, 2012).

effect, Vera Cossio & Contreras (2011)[4] evaluate the behavioral response triggered when BJP was made public but before disbursements began. They report a statistically significant increase in school attendance, particularly among low-income rural children. In our simulation, this parameter represents an incentive effect of program inclusion, independent of the cash receipt. Regarding the outcome effect, the remaining studies evaluate the ex-post impact of the realized transfer. Grigoli & Sbrana (2012)[5] and Canelas & Niño-Zarazúa (2018)[6] find that the transfer significantly boosts enrollment, especially in secondary school, but find no significant reduction in child labor; while Vera-Cossio (2022)[7] finds no significant effects of the BJP. The consistent lack of impact on child labor, and the positive labor supply effects noted in the broader literature, reflects the modest size of the BJP transfer (BOB200 per year). Rather than allowing households to withdraw children from work, the cash seems to rather relax liquidity constraints to cover fixed schooling costs (such as transport, stationery, books and other supplies) without being large enough to replace the child's economic contribution.

While in our simulations we use the arithmetic mean to describe and summarize the central tendency of these findings, we do not rely exclusively on it. Instead, we carefully account for the variability between studies accounting for richness and heterogeneity of this evidence. Importantly, we do not conduct a formal meta-analysis because several outcomes in Table 1 rely on a single estimate (Cohen, 1988; Glass, 1976) and because impact estimates are inherently heterogeneous due to program expansions and subgroup-specific evaluations (Deeks et al., 2008; Davey Smith et al., 1997). Rather, we exploit this variability by incorporating the minimum, mean, and maximum parameter values into our simulations. This allows us to test a range of scenarios, ensuring that our counterfactual allocation rules reflect the nuanced ways in which Bolivian households have responded to both the promise and the receipt of social transfers across different socioeconomic contexts.

3. Methods

3.1. Measuring multidimensional poverty: the Alkire-Foster method

Consider a set of n individuals and $j = 1 \ldots d$ relevant deprivation indicators. X is a $n \times d$ matrix that contains the entries for each individual in any indicator. This matrix can be transformed into matrix g^0, which translates the indicator value of individual i in any indicator j to $g^0_{ij} = 0$ if they are not deprived in that indicator, and $g^0_{ij} = 1$ if they are deprived.

[4] Vera Cossio and Contreras (2011) conduct an ex-post evaluation of the BJP effect, focusing on the announcement effect, rather than the transfer itself, on school enrollment, attendance, and child labor, with the aim of mitigating endogeneity and selection bias. The analysis covers children aged 5 to 17. To address selection bias, the authors estimate two biprobit models (one jointly modeling enrollment and work decisions, and another modeling school attendance and work) grounded in a leisure–income framework that assumes correlated time-allocation choices.

[5] Grigoli & Sbrana (2012) investigates the determinants of school enrollment, primary school attendance, and child labor for children aged 5 to 15 in Bolivia. Their study employs a trivariate probit model to jointly estimate the correlated decisions to enroll, attend school, and work. Although the authors acknowledge potential selection bias (since enrollment conditions the decision to attend school) they do not instrument the equations due to data limitations. As the BJP was introduced in 2006, the analysis captures its impact only in 2007, corresponding to the program's initial phase.

[6] Canelas & Niño-Zarazúa (2018) evaluate the impact of the BJP on schooling and child labor. The analysis covers adolescents aged 13–16 who have completed the second or third year of secondary education, being the first study to analyze its effects on secondary school-aged children. The authors apply a difference-in-differences strategy estimated by OLS, comparing a treatment group of individuals with eight years of schooling who received the BJP to a control group with nine years of schooling who never received the transfer.

[7] Vera-Cossio (2022) analyzes the effects of CCT on labor supply in Bolivia. Their study focuses on households with at least one school-age child enrolled in grades 1–8 in non-private schools, allowing comparisons over four years before and after the introduction of BJP. This study employs a difference-in-differences approach estimated by OLS for the outcomes relevant to BJP-eligible children.

Additionally, consider a vector $w = (w_1,..., w_d)$, representing the relative importance of each indicator, where the sum of these elements equals 1. As a result of combining matrix g^0 and vector w we get $c_i = \sum_{j=1}^{d} w_j g_{ij}^0$ for any individual i, which represents their deprivation score, that is, the number of weighted deprivations they suffer.

A multidimensional poverty cutoff k is needed to separate the poor from the non-poor individuals. The identification function $\rho\left(g_i^0, w, k\right)$, which takes a value of 1 if $c_i \geq k$ and 0 if $c_i < k$ identifies, respectively, who is multidimensionally poor and who is not.

This information can be aggregated to estimate $H = \frac{1}{n}\sum_{i=1}^{n} \rho\left(g_i^0, w, k\right)$, or the headcount ratio, which represents the incidence of multidimensional poverty in this set of individuals. It is also possible to calculate $A = \frac{1}{q}\sum_{i=1}^{n} (\rho\left(g_i^0, w, k\right) \times c_i)$, where q is the number of poor individuals, and represents the average of weighted deprivations experienced by the poor population, which is the intensity of multidimensional poverty. Finally, M_0 or the adjusted headcount ratio, can be calculated by multiplying H and A, $M_0 = \frac{1}{n}\sum_{i=1}^{n} (\rho\left(g_i^0, w, k\right) \times c_i)$, representing the average of deprivations weighted by their importance experienced by the poor population as a proportion of the total number of individuals, n. M_0 is regularly termed the Multidimensional Poverty Index (MPI, see Alkire & Foster, 2011) and for simplicity, we will denote it as M in the remainder of the paper.

We acknowledge that M as it is defined in here (strictly following Alkire and Foster, 2011) does not fulfill the strong transfer axiom[8] and is therefore not sensitive to the distribution of deprivations among the poor as opposed to the classes of indices proposed by Rippin (2017) or Datt (2019). However, we argue that it remains the most functional measure for our ex-ante policy simulation because of its direct additive decomposability. This axiomatic property allows the aggregate index to be expressed as the weighted sum of deprivations across all indicators, which is particularly advantageous for our framework. This mathematical transparency implies that a reduction in deprivation for a specific indicator results in a proportional and predictable reduction in the overall index, calculated as the sum of the changes in each dimension multiplied by their respective weights: $M = \sum_{j=1}^{d} w_j H_j(k)$, where $H_j(k)$ is the proportion of people that are poor and deprived in indicator j, or the censored headcount ratio of this indicator (Alkire and Foster, 2011).

[8] The strong transfer axiom requires that a regressive transfer, i.e. taking a resource from a poor person and giving it to a less poor person, must result in a strict increase in the poverty index, provided the transfer occurs between two poor individuals. In a multidimensional context, this means the index should be sensitive to the distribution of deprivations among the poor. While M_0 derived from the AF method satisfies dimensional monotonicity (poverty falls if a poor person becomes non-deprived in one dimension), it does not fulfill the strong transfer axiom because it is invariant to changes in how a fixed set of deprivations is distributed among the poor (Datt, 2019; Alkire & Foster, 2011).

By leveraging this property, we can precisely track how improvements in specific indicators, calibrated from the empirical literature that we have discussed, translate into aggregate poverty reductions. Furthermore, we argue that the objective of focusing on the most deprived is achieved in our analysis not through the endogenous properties of the index, but through the prioritarian allocation rules we posit, which use the intensity of deprivation to ensure vertical equity in resource distribution.

3.2. A proposed structure of an MPI for Bolivia

As we mentioned before, Bolivia remains one of the few countries in the region yet to adopt an official multidimensional poverty measure. While we do not intend to propose a definitive national index, we have meticulously developed a framework that incorporates the maximum number of indicators measurable via official Household Survey (2022) microdata. This measure reflects national priorities established in development plans and agendas, providing a realistic, albeit perfectible, instrument for our simulation analysis.

We have taken into consideration various global and regional poverty measures to benchmark our design. Among them, we draw inspiration on Santos & Villatoro (2016), who propose a regional MPI for Latin America that captures the specific deprivations common to the continent, and Alkire et al. (2023), who develop a moderate MPI framework tailored for countries that have moved beyond acute poverty. These frameworks were instrumental in selecting indicators and thresholds that exceed the thresholds of extreme deprivation, ensuring the measure remains relevant for Bolivia's current socioeconomic context.

Although an exhaustive discussion of the ideal Bolivia-specific MPI lies beyond the scope of this paper, it is important to acknowledge the constraints imposed by the available data. Our proposed index is strictly limited to the variables captured in the 2022 Household Survey. Thus we are unable to include all relevant dimensions of poverty for Bolivia, such as psychological well-being, empowerment, physical safety, and social participation (Alkire, 2007). While these dimensions are critical for a holistic understanding of human capability, they are absent from the microdata that we use here. Thus we insist we do not wish to posit a definitive national index, as that would require a broad political consensus and potentially new data collection instruments.

Thus our proposal comprises four dimensions, namely education, health, living standards, and work, each justified by theoretical grounding and empirical relevance as presented in Table 2. The first three dimensions replicate the core of the Global MPI (Alkire & Santos, 2014; Alkire & Jahan, 2018), whose alignment with the SDGs and rich theoretical literature make them a natural point of departure. Within the education dimension, we utilize two indicators, school attendance for children of official age and years of schooling for adults, which are defined to reflect Bolivia's Ley Avelino Siñani (2010)[9]. While these proxies do not capture educational quality, they represent the best available measures of educational deprivation and embody the notion of effective literacy, where a single educated household member can create benefits for all (Basu & Foster, 1998).

Health, likewise, is indispensable to human functioning but poses a measurement challenge given the data limitations. We constructed four health indicators, assisted delivery, access to health services, access to health insurance, and severe food insecurity. The latter is gauged by the FAO's Food Insecurity Experience Scale (Ballard et al., 2013). This set draws inspiration from national

[9] Law. 070 "Avelino Siñani–Elizardo Pérez" establishes Bolivia 's education system. It can be seen on: https://www.minedu.gob.bo/files/documentos-normativos/leyes/LEY_070_AVELINO_SINANI_ELIZARDO_PEREZ.pdf

MPI practices in Mauritania and the Dominican Republic (Sistema Único de Beneficiarios, 2020) to capture both acute and chronic facets of health deprivation.

While the living standards dimension often represents means rather than ends (Alkire & Santos, 2014), the indicators selected here serve as essential proxies for acute capability shortfalls. These indicators represent basic functionings that are both socially valued and highly responsive to policy. This dimension emphasises that infrastructure and service access are foundational to human development. The dimension includes seven household-level indicators: electricity, sanitation, drinking water, flooring, cooking fuel, and asset ownership, mirroring the Global MPI, plus overcrowding. The inclusion of overcrowding addresses specific housing pressures in Bolivia and is well-supported by literature as a critical driver of deprivation (Tekgüç & Akbulut, 2022; Cage & Foster, 2002).

Finally, recognizing Bolivia's highly informal labor market (Sehnbruch et al., 2020), we propose work as a fourth dimension. Four indicators gauge employment quality and youth protection, namely child labor below the legally prescribed age (Código Niña, Niño y Adolescente, 2014[10]), lack of formal contracts (as per Ley General del Trabajo, 1942[11]), unemployment, and pensions. By considering this dimension, we align with Sen's assertion that the right to work is a cornerstone to human freedom (Sen, 1999).

Table 2: A proposed MPI for Bolivia

Dimension (weight)	**Indicator**	**Weight**	**A household is deprived if…**
Education (¼)	School attendance	1/8	At least one school-aged child in the household does not attend school up to the age at which they should be in grade 8. In Bolivia, this age range is from 6 to 14 years old.
	Years of schooling	1/8	No household member aged 10 years or older has completed at least 6 years of schooling.
Health (¼)	Assisted delivery	1/16	At least one woman in the household who was pregnant in the five years prior to the interview was not attended by a doctor or nurse during childbirth.
	Access to health services	1/16	At least one household member who fell ill during the 12 months prior to the interview did not seek any healthcare services.
	Health insurance	1/16	No household member is covered by any type of health insurance.
	Food security	1/16	In the past 12 months, household members experienced hunger but did not eat and went an entire day without food due to a lack of money or other food resources.

[10] Law No. 548 (2014), the Child and Adolescent Code, establishes the rights and protections of children and adolescents in Bolivia. Available at: http://gacetaoficialdebolivia.gob.bo/normas/buscar/548

[11] The General Labor Law of Bolivia (1942) establishes the legal framework governing labor relations, workers' rights, and employment conditions in the country. Available at: https://www.oas.org/dil/Migrants/Bolivia/Ley%20general%20del%20trabajo%20del%208%20de%20diciembre%20de%201942.pdf

Living standards (¼)	Electricity	1/28	The household does not have electricity.
	Cooking fuel	1/28	The household cooks with dung, firewood, or charcoal.
	Sanitation	1/28	The household's sanitation system is either unimproved or improved but shared with other households.
	Drinkable water	1/28	The household does not have access to improved drinking water.
	Housing	1/28	The household has inadequate housing: the floor is made of natural materials, or the roof or walls are made of rudimentary materials.
	Overcrowding	1/28	The household has more than three people sharing a single habitable room.
	Assets	1/28	The household owns no more than one of the following items: radio, TV, telephone, computer, animal cart, bicycle, motorcycle, or refrigerator, and does not own a car or truck.
Work (¼)	Occupational status	1/16	No household member over the age of 14 is employed.
	Child labor	1/16	At least one household member aged 7 to 14 is engaged in work.
	Tenure	1/16	All household members aged 18 and older have been employed in their current occupation for less than 3 years.
	Pensions	1/16	No employed household member is enrolled in any pension system.

Note: The definition of improved sanitation is applied following WHO & UNICEF (2021). The definition of improved drinking water comes from UNICEF (2023). The housing and rudimentary materials definition follows UN-Habitat (2020) and Florey & Taylor (2016). Health services refer to Health Insurance Funds (Cajas de Salud), public and private health facilities, and home care provided under the "Mi Salud" program. However, self-care at home, traditional medicine, or self-medication following a pharmacy consultation are not included in this category.
Source: Own elaboration.

The weights for each dimension and indicator were chosen using the nested weights principle (Alkire et al., 2015), by which i) the weights for each dimension are the same (¼ in this case), and ii) the weights for each indicator have equal weight within their respective dimensions. We apply two poverty cutoffs following Alkire and Foster (2011). Our primary analysis uses $k = 1/4$ to identify multidimensional poverty, which represents households deprived in the equivalent of at least one full dimension. For robustness, we also evaluate a stricter $k = 1/2$ cutoff to capture extreme multidimensional poverty, defined as deprivation in two or more full dimensions.

3.3. The simulated allocation rules

Following the BJP framework, the pool of eligible individuals comprises i) all individuals enrolled in primary or secondary education in a public or agreement-based institution within the regular school system are eligible until they turn 21 years old, as well as ii) all individuals enrolled in the special education program, with no age restriction. Importantly, access to BJP is universal for all eligible children. We do not alter the actual eligibility rule, thus we assume a full participation rate. Rather, we adjust each eligible child's probability of being positively impacted by the program based on their poverty and deprivation conditions.

To operationalize the simulation framework, we define a success rate as the proportion of eligible children for whom program participation translates into the intended schooling-related outcome, such as continued school attendance or avoidance of child labor. Eligibility is defined exactly as in the BJP itself, by which children are eligible if they are formally enrolled in school. The success rate therefore captures the probability that an enrolled child effectively benefits from the transfer in the form of improved schooling outcomes. Rather than assuming that this probability is identical across all eligible children, we simulate how poverty outcomes differ when expected program effectiveness is prioritized toward more disadvantaged cases. Under the myopic rule, successes are assigned randomly among all eligible children. Under the prioritarian rules, the same total number of successes is concentrated among children living in households with higher multidimensional deprivation.

To ensure conceptual consistency, it is important to distinguish between the unit of eligibility and the unit of deprivation identification. BJP is an individual-level transfer conditioned on the school enrollment of specific children. In contrast, following standard practice in the AF framework, all deprivation indicators are identified at the household level (Alkire et al., 2015). Let us consider the school attendance indicator to explain this further – the similar logic applies for all BJP outcome indicators. A household is classified as deprived in school attendance if at least one enrolled child in the household is not regularly attending school (see Table 2). In the simulation, the transfer is always received by an enrolled child, but the resolution of a deprivation is assessed at the household level. If a deprivation in school attendance is lifted, it reflects that the household no longer contains any enrolled child who fails to attend school. The simulation does not assume an intrahousehold allocation of impacts. Rather, it captures whether the program succeeds in achieving its intended outcome for the eligible child, with poverty effects evaluated using household-level deprivation status.

To explain these rules in more detail, we stress that we explicitly recognise that the pool of eligible children in BJP is heterogeneous, with some facing a single deprivation, others multiple overlapping deprivations in the program's objectives, and others facing none. We thus explore the effectiveness of three allocation rules:

- *Myopic Rule:* Under this rule, the pool of potential beneficiaries is defined strictly by the program's legal eligibility criteria (enrollment in a public school) and inherently excludes households without school-aged children. However, because the BJP is currently universal within the public school system, this pool includes both multidimensionally poor and non-poor individuals. The myopic nature of this rule refers to its indifference to the joint distribution of deprivations because it assumes that the program's success rate is distributed randomly across this entire eligible population. This rule represents the current administrative reality of the BJP and serves as a good benchmark because it allows us to evaluate the efficiency gains of moving toward alternative rules.
- *Prioritarian Rule*: Under this rule, ethical priority is given to children who are worst-off, defined as those experiencing the highest number of overlapping deprivations. Specifically, it prioritizes eligible children that are identified as multidimensionally poor using a poverty cutoff of $\frac{1}{4}$ making sure that deprivations are lifted for these children first. This method aligns with the principle of prioritizing the most disadvantaged.
- *Extreme Prioritarian Rule*: Similar to the prioritarian rule above, this rule focuses on the worst-off children but uses a more stringent poverty cutoff of $\frac{1}{2}$ to identify children

living in severe multidimensional poverty and making sure that deprivations are lifted for them first. By concentrating resources and efforts on the most severely deprived, this strategy aims to maximize the program's effectiveness in addressing the needs of children living in critical conditions.

Importantly, the allocation rules that we defined do not assume that policymakers can directly decide which children benefit from the program. Instead, our microsimulations reallocates expected program effectiveness across eligible children to represent how limited implementation capacity or complementary resources may be prioritized in practice. The success rate should therefore be understood here as a measure of the likelihood that BJP participation translates into the intended program outcome, conditional on eligibility. Across all scenarios, legal eligibility, program coverage, and total resources are held constant. We do not model budget changes in BJP, only the way expected effectiveness is distributed across eligible children.

In practice, differences in expected effectiveness can arise from several implementable policy choices. These include differentiated transfer amounts (for example, top-ups for children facing multiple deprivations), differences in implementation effort (such as more reliable payments, targeted outreach, or closer school follow-up), and the selective bundling of cash transfers with complementary services, including transport, school supplies, or nutrition support. Our simulations do not purport to model these policy choices. Rather, we evaluate the efficiency implications of prioritizing such limited resources toward children experiencing higher overlapping deprivations.

From an ex-ante policy design perspective, we argue this abstraction is appropriate because our goal is not to estimate the causal impact of any specific implementation mechanism, but to compare how alternative allocation rules perform under a fixed budget and eligibility structure.

3.3.1. Formal aspects

To understand the formal underpinnings of our simulation framework, let us first focus on any one of the program's several intended outcomes; we will omit the indicator index for notational clarity. We remind that the success rate is defined as the proportion of eligible children who experience a positive program impact, functioning as the parameter we distribute among the eligible children to evaluate poverty reduction.

We understand that simply taking the mean to calibrate the expected program's success rate masks important heterogeneities around this parameter. We thus use the most out of the available information in the key impact references to also consider i) the minimum and maximum documented success rates, respectively, as well as ii) the documented subnational heterogeneity, such as differentiated success rates in urban and rural areas, age cohorts, sex, etc[12]. For simplicity, let us denote the success rate of the program as p^0, which can be parametrized as $p^0_{National,\,mean}$, $p^0_{National,\,min}$ or $p^0_{National,\,max}$ using national-level impact estimates or as $p^0_{S,mean}$, $p^0_{S,min}$ or $p^0_{S,max}$ using impact estimates found for subgroup S, which can be urban and rural regions, provinces, age cohorts, sex, etc[13].

[12] We reiterate that we do not conduct a meta-analysis because some outcomes rely on a single estimate (Cohen, 1988; Glass, 1976) and because impact estimates are heterogeneous due to program expansions and subgroup-specific evaluations (Deeks et al., 2008; Davey Smith et al., 1997). Instead, we exploit this variability by using the minimum, mean, and maximum parameter values in the simulations.

[13] The specific parameterizations for each simulation are reported in Tables A1.1, A1.3 and A1.5 in Appendix 1.

The three allocation rules that we study here differ in the way the natural heterogeneity in the pool of eligible children is taken into account. Let us denote the set of eligible individuals as *N* of cardinal size *n*. The *myopic* rule assigns a uniform success rate to every child $i \in N$. Let us denote by π_i the binary indicator signalling success of the program for child i in any given program objective or indicator. We assume that π_i is distributed following a Bernoulli distribution. For instance, if we parametrize the program's success rate with the documented mean national-level estimates, then $\pi_i = 1$ with probability $p^0_{National,\,mean}$, and $\pi_i = 0$ with probability $1 - p^0_{National,\,mean}$ for all $i \in N$. Thus, the number of children that can be expected to be positively impacted by the program is denoted genetically as np^0, that is the number of eligible individuals times the success rate of the program.

The *prioritarian rule* divides the eligible population in subgroups defined by their poverty condition and the number of overlapping BJP deprivations they face, which we will denote as $r = 0,.., R$. As in the myopic rule, all the eligible children participate in the program and its success rate remains unchanged and exogenously determined. This ensures that the number of individuals that can be expected to be positively impacted by the program remains np^0. Under this rule, however, we assume that positive impacts are not randomly distributed. Rather, they are assured sequentially giving priority to those that are worse-off.

- First, the program focuses on all individuals that are multidimensionally poor (with $k = 1/4$, meaning that they suffer deprivation in at least 25% of the weighted deprivations in the proposed MPI) and suffer the maximum number of BJP deprivations R. Let us denote the set of individuals living in these conditions as $F_R \subset N$ of cardinal size $f_R < np^0$. For all individuals $i \in F_R$, $\pi_i = 1$ meaning that the program eliminates their deprivation.
- Next, we assume that the program turns focus on those that are multidimensionally poor and have a number of deprivations $R - 1$. All individuals in these conditions belong to the set F_{R-1} of cardinal size f_{R-1}.
    - If $f_{R-1} \leq np^0 - f_R$, then $\pi_i = 1$ for all individuals $i \in F_{R-1}$. This means that the program also lifts deprivations for all individuals in this set, and only then it shifts focus onto individuals i in F_{D-2} sequentially.
    - However, if $f_{R-1} > np^0 - f_R$, then we cannot assume that there is credible evidence that the program will positively impact all individuals in F_{R-1}, but only a fraction $(np^0 - f_R)\,/\,f_{R-1}$ of them. In this case, we assume that the binary indicator of program success, π_i, follows a Bernoulli distribution for all individuals $i \in F_{R-1}$ with an adjusted success rate $(np^0 - f_R)\,/\,f_{R-1}$
- This sequence continues assuming that $\pi_i = 1$ for all priority subgroups in decreasing order of overlapping BJP deprivations until only a fraction of the priority subgroup in turn can be positively impacted by the program according to the academic evidence of its success. Again, for this subgroup, π_i follows a Bernoulli distribution with a success rate defined by the ratio between i) the number of remaining individuals that can be

realistically expected to be lifted out of deprivation by the program and ii) the number of individuals belonging to the subgroup in turn.

The *extreme prioritarian* rule follows a similar logic, but focuses on those individuals that live in severe multidimensional poverty first ($k = 1/2$), meaning that they face deprivations in half or more of the weighted indicators in the MPI for Bolivia). After all the individuals living with these severe hardships have been positively impacted by the program, attention is shifted towards those that live in multidimensional poverty ($k = 1/4$). As in the prioritarian rule, the number of individuals that is expected to be positively impacted by the program remains unchanged and exogenously determined (np^0). Similarly, the program success rate is adjusted to parametrize a Bernoulli distribution for π_i for the subgroup that can only partly be impacted by the program after deprivations were lifted for the worse-off[14].

These three allocation rules are applied for each program outcome one at a time. This implies that we assume independent impact across indicators, which represents the lack of existing evidence about the magnitude of simultaneous BJP impacts for the same individuals in the existing literature[15].

3.3.2. Intuitive explanation of the prioritarian allocation rules

Intuitively, the prioritarian rule operates by ordering the eligible population according to the cumulative intensity of their deprivations across the three BJP outcomes included in the MPI: school attendance, years of schooling, and the avoidance of child labor. This hierarchy ensures that the order of resource allocation is determined by the joint distribution of these hardships, moving systematically from those facing more hardships to those facing fewer.

The *first* tier of resources is strictly directed toward children that live in multidimensional poverty ($k = 1/4$) while experiencing a triple overlap of deprivations. These are individuals who are simultaneously out of school, lagging behind in their expected educational attainment for their age, and engaged in child labor. Once this most acutely deprived group has been served, the allocation logic moves to a *second* tier of beneficiaries consisting of those living in multidimensional poverty and suffering from any combination of two deprivations. The *third* priority is subsequently assigned to those in multidimensional poverty and experiencing only a single form of deprivation among the three indicators. A *fourth* priority group is established for children who meet the BJP legal eligibility criteria, live in multidimensional poverty but do not face any of the three specific BJP deprivations. Finally, a *fifth* priority group is formed by children that are eligible but not multidimensionally poor, nor suffering deprivation in any BJP indicator. Children in the fourth and fifth groups are served only after the needs of all deprived subsets have been met and provided that the program's capacity or success rate allows for further coverage.

[14] A visual representation of how each allocation rule operates within the BJP microsimulation framework is provided in Appendix 1.

[15] In our simulation framework, the procedure for eliminating deprivations varies by indicator. For school attendance and child labor, we directly apply the program's success rates to the probability of being deprived in these indicators. The years of schooling indicator, however, requires a more nuanced approach. While the BJP operates by increasing enrollment (a flow variable), this only translates into a reduction in years of schooling (a stock deprivation) for specific students. In our setting, the deprivation in years of schooling is eliminated only for beneficiaries aged 10 or older who, by completing this additional year (having already finished five), effectively cross the deprivation threshold. This is based on the assumption that successful enrollment results in the completion of the full school year. This may appear to be a strong assumption, but it is plausible given that Bolivia's dropout rate is currently less than 1.9%. This and other Bolivian education indicators can be found at: https://seie.minedu.gob.bo/reportes/indicadores).

The extreme prioritarian rule follows a sequential prioritization that combines deprivation in BJP-relevant outcomes with overall multidimensional poverty status. Allocation begins with children who are both severely multidimensionally poor and deprived in at least one BJP-relevant indicator. Within this group, children are served in descending order of the number of overlapping BJP-related deprivations, with highest priority given to those simultaneously out of school, lagging in years of schooling, and engaged in child labor, followed by those with two deprivations and then those with one.

Once all severely poor children with BJP-relevant deprivations are covered, the same prioritization logic is applied to children living in multidimensional poverty using the $k = 1/4$ threshold. Again, allocation proceeds in descending order of BJP deprivation intensity within this poverty group. After all poor children with BJP-relevant deprivations have been served, any remaining program successes are allocated to eligible children who are not deprived in BJP-related indicators, prioritizing first those in severe poverty, then those in poverty by $k = 1/4$. Children who are not multidimensionally poor are served only if resources remain after these priority groups are exhausted.

By structuring the distribution of the program's success rate in this manner, both prioritarian rules replace the random probability of a myopic system with a logic of vertical equity, ensuring that the depth of a child's poverty is the primary driver of the social protection response[16].

A critical feature of our framework is that while we use the overall deprivation score (c_i) to identify the poor, we prioritize allocation based specifically on the count of BJP-relevant deprivations. We adopt this domain-specific logic to ensure policy coherence. Relying solely on the aggregate deprivation score to determine priority could theoretically divert resources to households that are intensely deprived in dimensions such as housing or health but face no immediate deficits in education. Such an allocation would misalign the specific instrument (an education-conditional transfer) with the specific burdens it aims to tackle. By focusing the count of deprivations we ensure that the program benefits first to those suffering most acutely from the specific conditions the program was designed to alleviate.

3.4. The empirical operationalisation of the simulation framework

To assess the performance of the three proposed allocation rules – myopic, prioritarian and extreme prioritarian – we compare the resulting levels of multidimensional poverty once each of them have been applied using different parameterizations. We depart from the situation prior to any simulated BJP intervention. We then compare this scenario with a set of simulated levels of multidimensional poverty resulting from the implementation of the program under the three allocation rules that we have defined. Please note that for each rule, we have used all the available information in Table 1 to credibly parametrize the program success rate (the mean, maximum, and minimum values, at the national level and all reported subnational levels).

In the baseline and all simulations, levels of multidimensional poverty are measured in three ways (see Alkire and Foster, 2011): i) the proportion of people living in multidimensional poverty, denoted as H, ii) the average number of weighted deprivation that the poor people suffer, denoted as A, and iii) the combination of both measures namely the multidimensional poverty headcount ratio adjusted by the intensity of poverty, denoted as $M = H \times A$. We will denote as

[16] Visual representations of the priority tiers/groups within the BJP-eligible population for the prioritarian and extreme prioritarian rules are shown in Figures A1.2 and A1.4 in Appendix 1.

M^s, H^s, A^s the resulting levels of multidimensional poverty after simulation s, with M^0, H^0, A^0 representing the initial levels prior to any simulation.

To allow for more robust comparisons between the initial scenario and simulated results, non-parametric bootstraps are used to operationalise the simulated allocation rules (Efron & Tibshirani, 1993; Hesterberg et al., 2003). Each bootstrap simulation consists of 100 repetitions and is specific to one program outcome, one allocation rule, and one parameterization for it. This procedure allows us to make adequate statistical inferences about the performance of each rule. Chiefly among them is establishing the significance of poverty reductions obtained from each allocation rule. To evaluate changes in the M or H statistics, a paired t-test is used to compare initial and simulated results, exploiting the fact that the compared samples have the same number of observations (Newbold et al., 2013). Since all simulations and bootstrap procedures are conducted using the same sample, simulated results are not independent and the standard errors take this nuance into account. Evaluating changes in A poses an additional complication because the samples used are of different sizes. Indeed, the average deprivation among the poor and those that are identified as poor change in each simulation. To avoid overestimating the real covariance, the Welch's t-test also termed the unpaired t-test, is used instead (Welch, 1947; Newbold et al., 2013)[17].

4. Data

We use microdata from the official and publicly available Household Survey (2022). This dataset is ideal for our study because it explicitly includes questions about the receipt of various social protection instruments, including BJP. It contains information from 40,955 persons living in 12,535 households. This sample expands to 12,224,110 people living in Bolivia in 2022, and it is representative of the population at the urban/rural levels as well as the country's nine departments.

We use primarily an MPI with a poverty cutoff ($k = 1/4$). The initial situation, prior to any simulation, is presented in Table 3: 28.16% of the population is identified as multidimensionally poor, with an average deprivation intensity of 32.7%, resulting in an MPI of 0.092. For completeness, results for severe multidimensional poverty, where 1.05% of the population is poor, average deprivation reaches 55.52%, and the MPI equals 0.006, are reported in Appendix 3.

Table 3: Multidimensional poverty in Bolivia in 2022 with k=1/4

M=HxA	H	A
0.092	28.16%	32.70%
(0.0036)	(0.97)	(0.33)

Notes: Standard errors in parenthesis.
Source: Own elaboration with data from INE (2024).

The prevalence rates of each BJP deprivation in the MPI indicators are shown in Table 4. Following Alkire et al. (2015) and Alkire and Foster (2011), we make a difference between the proportion of people suffering deprivation in each indicator irrespective of their poverty status

[17] The Welch t-test adjusts the standard error and degrees of freedom to account for unequal variances and sample sizes. It calculates a t-statistic using group means, variances, and sizes, then assesses statistical significance using a modified t-distribution.
$t = (X_1 - X_2) / sqrt(s^2_1/n_1 + s^2_2/n_2)$

(i.e. the uncensored headcount ratio), and the proportion of people deprived in each indicator and are multidimensionally poor. (i.e. the censored headcount ratio, which naturally depends on the chosen poverty cutoff). More than 23% of the population live in a household deprived in the school attendance indicator; however, only 18% of the population live in households that face this deprivation and are multidimensionally poor (k=25%). This means that around 5% of the population live in households that face deprivation in school attendance, but they are not multidimensionally poor. Deprivation in years of schooling is relatively less frequent (5.79%), but it is a much more distinctive characteristic of people living in multidimensionally poor households – nearly all people living in households that face deprivation in years of school are also poor. Data show a similar pattern for child labour deprivations; 3.9% of the population live in a household facing this problem, and 3.4% of the population live in poverty and facing this problem[18].

Table 4: Censored and uncensored headcount ratios in 2022 for BJP-relevant indicators

Indicators	2022	
	Uncensored headcount ratio	**Censored headcount ratio (*k*=1/4)**
School attendance	23.75%	17.94%
Years of schooling	5.79%	5.01%
Child labor	3.87%	3.38%

Note: Censored and uncensored rates are not exclusive and they reflect national headcount ratios.
Source: Own elaboration with data from INE (2024).

In 2022, nearly 25% of Bolivia's population met the BJP's eligibility criteria, while almost 60% lived in households potentially impacted by the program, highlighting its broad reach. Nearly 45% of eligible individuals were not multidimensionally poor and did not suffer deprivation in the program's outcomes[19]. However, nearly half of the eligible population faced one or more deprivations in these outcomes, confirming untapped potential for poverty reduction if the program is better focused.

Out of all the people living in multidimensional poverty (by ***k*=¼**), 76% live with at least one BJP-eligible member, while 38.52% of eligible individuals live in poverty . Moreover, the proportion of eligible poor individuals suffering at least one deprivation is 70.12%, meaning that those who were free from these deprivations is 29.88% (see Figure A2.3 in Appendix 2). This already shows that prioritizing these households could be highly effective in reducing multidimensional poverty. In a within-country description, the rural population is overrepresented in the BJP-eligible poor population (58.17%), reinforcing the effectiveness of rural targeting to maximize impact. Gender-wise, a priori there is no significant advantage in prioritizing one gender over the other for poverty reduction as a similar proportion of women live in poor and non-poor households[20].

5. Results

To provide a comprehensive view of our results, we organized our findings into two distinct scenarios. The optimistic (upper bound) scenario includes all available data for calibration in Table 1, even those results that showed a very high impact because they focused on especially

[18] Importantly, less than 1% of the population live in a household that faces school attendance, years of schooling or child labor deprivations and live in extreme multidimensional poverty (k=1/2). See Table A3.2 in Appendix 3.

[19] Eligible individuals living in extreme multidimensional poverty account for roughly 1.8% of all eligible beneficiaries and 0.4% of the total population. See Figure A2.1 in Appendix 2.

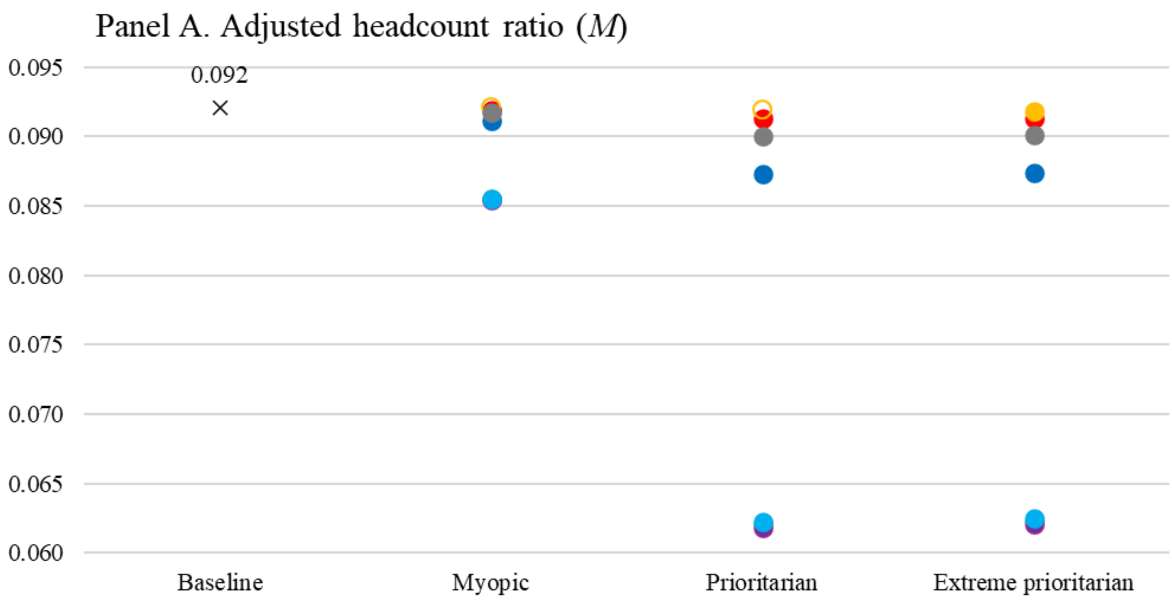
[20] The number of deprivations experienced by BJP-eligible individuals, disaggregated by area and sex, is presented in Figures A2.2, A2.4, and A2.6 in Appendix 2.

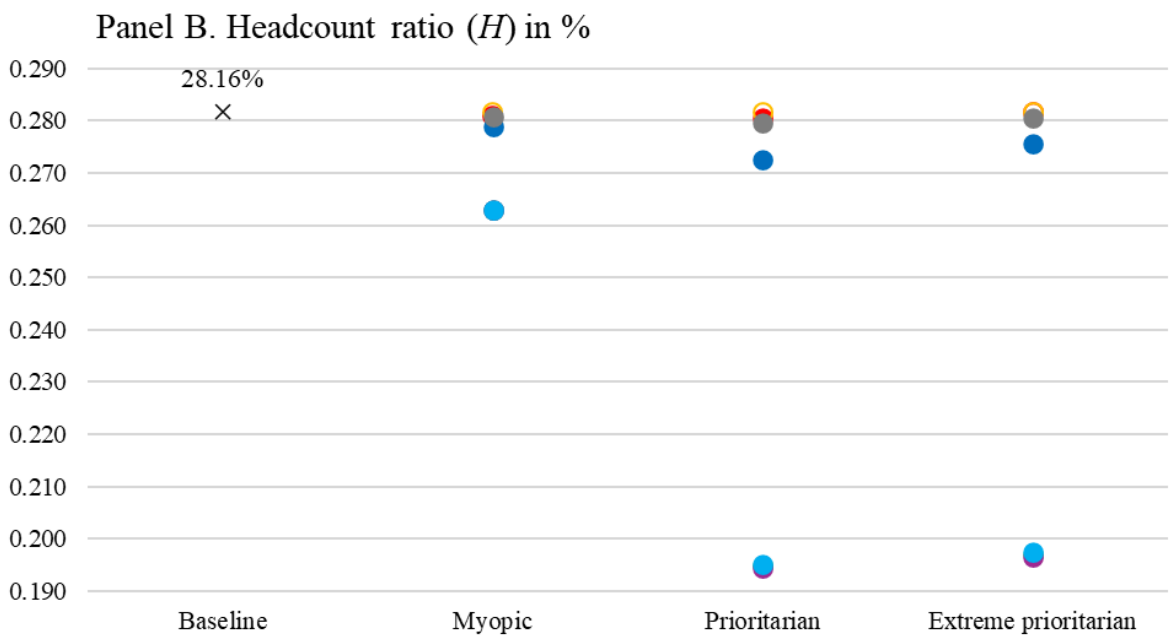
vulnerable, low-income groups. The realistic scenario is more cautious; it sets those high-end results aside to focus on broader, more conservative trends. This ensures that our conclusions are not just based on best-case settings but reflect a grounded realistic expectation of how the program performs.

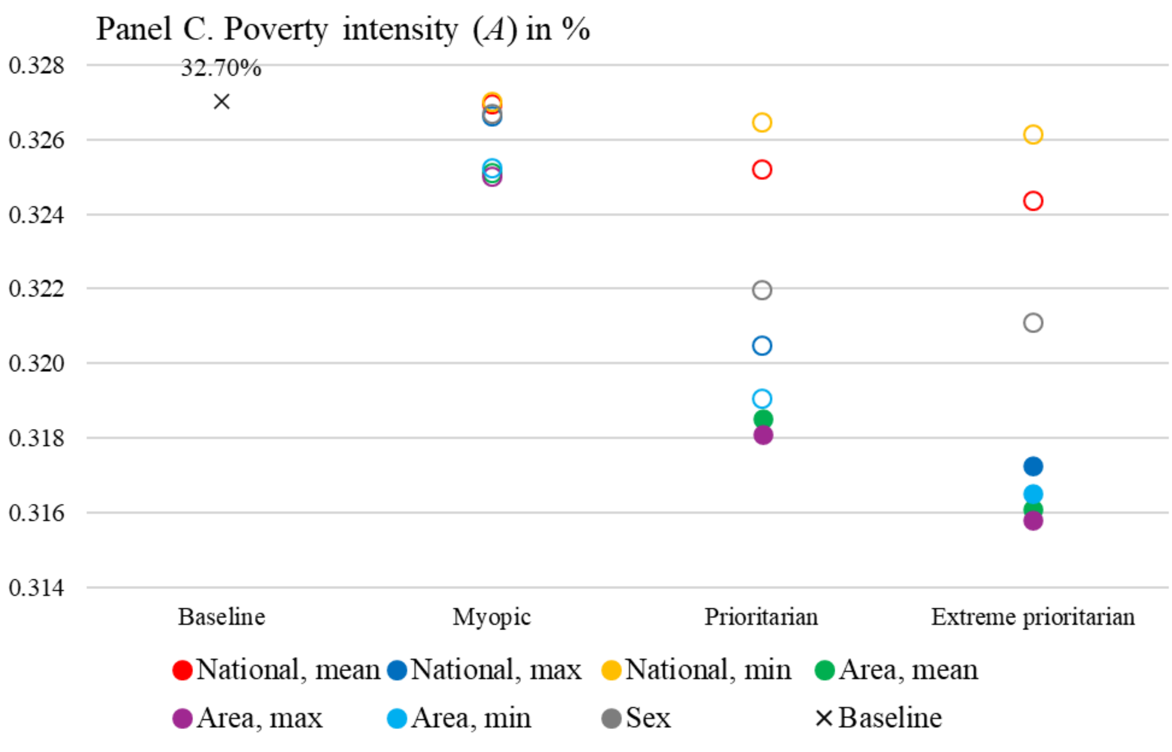
Our results show a clear and consistent pattern in that rules that prioritize the most deprived families lead to much larger and more meaningful drops in poverty than the myopic approach. In fact, our simulations suggest that when the program allocates resources without focusing specifically on those with the most needs, its impact on poverty can be so small that it is not statistically significant.

As shown in our results for multidimensional poverty ($k = 1/4$), prioritizing the most vulnerable children achieves a double benefit. It reduces the headcount ratio (H), meaning fewer people are living in poverty, and it also reduces the intensity (A), meaning that those who remain poor are suffering from fewer simultaneous deprivations. By focusing on the joint distribution of hardships and serving first the children who are facing multiple problems at once, the program clearly becomes a far more powerful tool for social change.

Figure 1: Simulated aggregate measures under different allocation rules and parametrizations (MPI with k=1/4, with 2022 data)







Notes: The X symbol denotes the baseline value of each statistic. Colored dots represent simulation outcomes under each allocation rule and parameterization. Filled dots indicate results that are significantly lower than the baseline, while hollow dots indicate results that are not significantly different from the baseline at the 5% significance level. Corresponding coefficients and p-values are reported in Tables A2.1, A2.2, and A2.3 in Appendix 2. Dot colors identify the parameterization used in each simulation for each allocation rule, as shown in Figures A1.1, A1.3, and A1.5. *National, mean* indicates calibration using national-level mean parameters from Table 1; *Area* and *Sex* denote calibrations based on area- and sex-specific parameters, respectively; and *max* and *min* refer to the maximum and minimum parameter values drawn from Table 1.
Source: Own elaboration (2024).

The prioritarian rule is found to be the most effective in reducing the proportion of people living in multidimensional poverty (*H*). This rule yields a reduction of 0.91 percentage points (pp) using realistic national success rates, and this reduction can go up to 8.73 pp using the most optimistic area-specific success rates. The extreme prioritarian rule reduces H by 0.61 pp and 8.5 pp, respectively. In turn, the myopic rule achieves reductions of only 0.26 pp with the realistic parameterization and up to 1.87 pp in the most optimistic one.

In fact, we find that none of the myopic rules yield statistically significant impacts on multidimensional poverty intensity (A). The only significant reduction of A under realistic assumptions is achieved by the extreme prioritarian rule, which reduces this measure by 0.98 percentage points. Under optimistic simulations, the prioritarian rule reduces A by 0.89 pp, while the extreme prioritarian rule achieves a reduction of 1.22 pp.

Combining the results on incidence (H) and intensity (A) and considering all parameterizations, both prioritarian rules reduce M_0 by up to 0.03 points, while the myopic rule reduces it only by 0.0067 points.

A robustness analysis allows us to infer that the efficiency gains identified in our analysis are not merely driven by the specific poverty threshold $k = 1/4$ but hold across broader multidimensional poverty thresholds. We performed our simulations focusing on the subpopulation living in severe multidimensional poverty as defined by the cutoff threshold $k = 1/2$ (see Appendix 3). This group represents a hard core of accumulated deprivation, characterized by an average intensity of 55.5%, which can make lifting these households out of poverty structurally difficult. Indeed, this rigidity can explain why none of our simulations yielded a significant reduction in poverty intensity (A) for this specific group. However, when analyzing the headcount ratio (H) and the overall adjusted headcount (M_0), the comparative efficiency of the allocation rules remains entirely consistent with our previous results.

As detailed in Figure A3.1 in Appendix 3, the extreme prioritarian rule continues to outperform all alternatives even for this severely disadvantaged group of children, reducing severe poverty incidence (H) by 0.98 percentage points. This is a marked improvement over the myopic rule, which achieves a reduction of only 0.15 percentage points even under optimistic assumptions. The superiority of the prioritarian rules over the myopic one, even within the most severe tail of the distribution, strongly reinforces one of our core messages, namely that the efficiency gains derived from vertical equity are robust and hold true regardless of the poverty threshold applied.

To better understand the mechanics of why our prioritarian rules outperform the myopic one, it is useful to unpack the simulated changes to the aggregate measures by using the additive decomposability axiom of AF-based measures (Alkire and Foster, 2011). We distinguish between changes in the uncensored headcount ratios (the raw proportion of the population deprived in a specific indicator) and the censored headcount ratios (the proportion of the population that is both deprived in that indicator and multidimensionally poor). This distinction also acts as a crucial validity test for our simulations.

Given the educational focus of BJP, our simulations only directly affected deprivations in the school attendance, years of schooling, and child labor indicators. Theoretically, the uncensored deprivation rates for the other non-treated indicators, such as housing, sanitation, or cooking fuel (see Table 1) should remain invariant across all allocation rules[21]. However, the censored rates for these dimensions should fall if the allocation rules effectively lift households out of multidimensional poverty. This is precisely what happens; all the results of this dimensional

[21] Note that the uncensored headcount ratios for the treated indicators (those related to BJP) may differ by scenario, even if they are parametrized in the same way, but this is solely due to survey sampling variation induced by the bootstrap procedure, which is inevitable during our simulations but largely non-significant.

disaggregation are presented in Appendix 4 and confirm this mechanism across multiple non-treated indicators.

First, consider the housing indicator, a structural deprivation representing the quality of floors, walls, and roofs. As expected, the uncensored headcount ratio remains constant for this indicator at 18.14% across all scenarios, confirming that our simulation framework does not artificially affect non-targeted indicators. In this case, our simulations do not imply, say, reconstruction of homes. However, an important divergence appears in the corresponding censored headcount ratios. Under the myopic rule, in the optimistic scenario, the censored headcount for housing is 8.61%. Under the extreme prioritarian rule, this figure drops to 7.27%. This reduction shows that BJP has an increased poverty reduction effect under the extreme prioritarian rule. By concentrating transfers on the most deprived, this allocation rule resolves enough deprivations (whether it be in education or child labor indicators) to push households of beneficiary children below the multidimensional poverty cutoff. Our results show that this happens more frequently under the prioritarian rule than myopic rule. This is the only reason why we observe a sharper decrease of the censored headcount ratio in, say, the housing indicator under the prioritarian rule.

A similar pattern is visible for the sanitation indicator. The raw proportion of the population lacking adequate sanitation remains fixed at 27.52% for all simulations. Yet, while the myopic rule results in a censored headcount of 13.18%, the extreme prioritarian rule drives this down to 11.07%. This corroborates that there are clear efficiency gains under the prioritarian allocation rules, which systematically perform better in lifting households out of the multidimensional poverty set.

For the specifically treated indicators in our simulation, the prioritarian rules generate larger direct gains, as well. Taking the child labor indicator as an example, the allocation rules affect both the incidence of the deprivation itself and potentially the poverty status of the household. Under the myopic rule, the uncensored headcount for child labor is 3.63%, with a censored headcount of 3.09%. The extreme prioritarian rule reduces these figures much more aggressively: the uncensored rate drops to 2.10% and the censored rate to just 1.39%. This dual reduction confirms that the prioritarian approach is doubly effective: it resolves the specific deprivation more frequently among the poor (lowering the uncensored count) and, by doing so, it is more effective in helping some of those households exit multidimensional poverty entirely (further lowering the censored count).

6. Concluding remarks

In this study, we aimed to provide a methodological contribution to the design of social protection systems, using the case of Bolivia's CCT Bono Juancito Pinto (BJP) to demonstrate the efficiency gains of taking a multidimensional approach to targeting. Our simulation results consistently showed that while the BJP is able to promote a reduction of multidimensional poverty in its current form, its impact can be significantly amplified through refined allocation rules. Thus, the alternative allocation rules may yield results that are more compatible with the aim of BJP in the long-run, which is precisely to reduce poverty. Most notably, we have shown that prioritarian allocation of transfers that concentrate resources first on households living with the most severe count of overlapping deprivations, consistently outperform the current uniformly allocated administrative payout of BJP, which we have termed a myopic allocation rule.

Under realistic parameterization, the prioritarian rule proposed here reduces the poverty headcount ratio by 0.91 percentage points, compared to a modest 0.26 percentage points under the myopic rule. This gap widens substantially in optimistic scenarios, where the prioritarian reduction reaches 8.73 percentage points. Crucially, while the myopic rule fails to yield statistically significant reductions in poverty intensity, the extreme prioritarian rule achieves a meaningful reduction of 0.98 percentage points in the realistic scenario. Consequently, the prioritarian rules drive a total reduction in the MPI of up to 0.03 points, nearly five times the maximum reduction achieved by the myopic rule (0.0067 points).

We have explained that this efficiency stems from a multidimensional poverty reduction mechanism visible in the decomposition of censored headcount ratios, which is one of the main axiomatic properties of AF-based multidimensional poverty measures. By concentrating resources on the most deprived, the prioritarian rules resolve specific deprivations, such as child labor, where the censored headcount ratio drops to 1.39% versus 3.09% under the myopic rule, while simultaneously pushing households across the poverty threshold. This effect spills over into non-targeted indicators. For instance, the censored deprivation ratio for sanitation falls to 11.07% under the extreme prioritarian rule compared to 13.18% under the myopic rule. These results confirm that prioritizing households with accumulated deprivations is the most effective strategy for resolving not just individual indicators, but multidimensional poverty as a systemic condition. Thus, our analysis also shows how simulation exercises can be used within the standard AF logic, as well as how to evaluate aggregate poverty changes through shifts in the censored deprivation headcount ratios.

It is important to qualify the nature of these targeting improvements. By holding the BJP's eligibility rule constant (public school enrollment), our study does not directly tackle exclusion errors at the extensive margin (i.e., recruiting out-of-school children). The eligibility rule is taken as a given, and instead, we focus on the efficiency of the allocation rule. In doing so, we indirectly address the fiscal consequences of inclusion errors. In a wide, universal program where resources often leak to the non-poor within the eligible population, our proposed prioritarian rules mitigate this inefficiency not by excluding the non-poor, but by minimizing the share of the budget they receive from the program. We argue that if a program aims to both improve wellbeing and reduce poverty, it is not necessary to exclude the non-poor from the eligible population, provided that program implementers are able to ensure that the bulk of the program's monetary effort is concentrated on those with the most disadvantaged deprivation profiles.

A distinct methodological feature of our analysis is the use of nationally representative household survey data rather than administrative registries. While this choice was partly motivated by data accessibility, it underscores a key advantage for ex-ante policy evaluation. Household surveys capture the full heterogeneity of the population and enable the construction of transparent, replicable multidimensional poverty profiles. This approach serves as a robust template for other low- and middle-income countries where administrative records may be fragmented or where targeting algorithms lack public documentation.

Nonetheless, we acknowledge specific data limitations in our study. While our reliance on exogenous, credible impact parameters found in credible academic literature minimizes the risk of over- or underestimating the program's aggregate success, it restricts our ability to uncover more granular heterogeneities. Future research should aim to disaggregate these impacts, for instance by subnational region or gender, to provide deeper insights into the specific distributional implications of the program.

Also looking forward, this study opens a significant avenue for research regarding the axiomatic refinement of allocation priorities. While we rely on the simplest version of the class of poverty indices that can be derived from the standard Alkire-Foster framework (namely M_0), which is distribution-neutral among the poor, future inquiries should incorporate distribution-sensitive multidimensional measures, such as other members in the Alkire-Foster class of poverty measures or those proposed by Rippin (2017), Datt (2019), Burchi et al. (2021). These indices have the advantage of explicitly accounting for inequality within the poverty set, albeit at the cost of relinquishing direct additive decomposability. Simulating allocation rules against these measures could test whether prioritarian transfers offer even greater resilience for the most deprived than our current results suggest, bridging the gap between practical policy tools and theoretical rigor.

Beyond our specific findings, we strongly advocate for the adoption of official multidimensional national poverty measures tailored to specific contexts and realities of the country. We have shown that such metrics are essential for designing policy interventions that reflect the true complexity of the population's deprivations. As Bolivia currently lacks an official multidimensional poverty standard, the measure proposed may offer a foundational starting point for this critical dialogue, but we do not claim it is the only possible or the ideal measure. What is of the essence here is that our analysis demonstrates that multidimensional measures should not be viewed merely as monitoring tools, but as active instruments for policy design. By moving beyond income thresholds and recognizing the interlinked disadvantages people face, a multidimensional measure can truly serve as a guide to action against poverty. Moreover, we advocate for the institutionalization of such measures, supported by panel data collection, to ensure that social protection systems effectively reach those that are at risk of being left behind in the development process.

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