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ABSTRACT

Efficiency in Poverty Reduction: A State-Level Analysis for Bolivia*

A decline in poverty generally masks regional disparities that are due to varying efficiency among states. Using a generalized true random-effects model, we distinguish between persistent and transient inefficiencies on subnational efficiency to reduce poverty and its determinants in Bolivia. Our findings reveal that states differ in terms of efficiency, with some excelling and others facing challenges. Persistent inefficiency emerges as pivotal, emphasizing the need for long-term policy recalibration. We find that when the macroeconomic conditions in Bolivia allow for a 10 percent reduction in the poverty rate, states can achieve at most an 8.2 percent reduction, and on average, they reduce it by 7.3 percent. Efficiency correlates positively with the tertiary sector's size; relationships with the primary and secondary sectors depend on their size, showing positive associations only if these sectors are fairly large. Additionally, states with lower unemployment and informality tend to be more efficient, highlighting the labor market's crucial role.

JEL Classification: C23, D63, I32, O41

Keywords: poverty, Bolivia, efficiency analysis

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1 Introduction

Despite facing various challenges and setbacks, the global landscape has witnessed a significant reduction in poverty. Measured at \$2.15 a day, poverty has declined globally from nearly 60 percent in the 1950s to around 10 percent as of 2022 (World Bank, 2023). However, despite this overall achievement, disparities persist across regions, with South Asia and Latin America and the Caribbean making substantial strides in poverty reduction, while Africa lags behind. These regional dynamics are also mirrored at the subnational level, with some subnational governments making significant progress in poverty reduction while others struggle to keep pace. These variations reflect the efficiency with which states utilize their resources (Barrett et al., 2005; Heady, 2000), differences in the policies implemented (Liu et al., 2021), and the macroeconomic conditions faced by states (Agénor, 2005; Walton, 2009; Ferreira et al., 2010; Garba et al., 2016).

Although considerable strides have been made in understanding regional heterogeneity in poverty dynamics (Morelli et al., 2015; Da Costa and Dias, 2015), there is limited knowledge regarding the technical efficiency of states in poverty reduction and its determinants. Efficiency with regard to poverty reduction in this context can be understood as a state's ability to reduce poverty given certain conditions (inputs), such as institutional factors, expenditure on social programs, investment, and macroeconomic conditions. [1]. The estimation of efficiency and its determinants will not only enable governments to better target efforts toward states with higher unmet potential for poverty reduction, it will also identify factors where reallocating resources could enhance states' poverty reduction.

Following Ravallion and Datt (1996), Ferreira et al. (2010), and Canavire-Bacarreza et al. (2018), we propose an empirical framework that enables the disentangling of the efficiency in poverty reduction at the subnational level and its determinants and apply it to a country case study, Bolivia. However, we depart from the existing literature by relaxing the assumption that states are fully efficient at reducing poverty. Instead, we make use of a generalized true random-effects model (GTRE) that enables the estimating of efficiency and the decomposing of it into persistent efficiency (the part related to structural problems) and transient efficiency (the part due to nonpersistent problems that can be solved in the short term).[2] In addition, we apply the binscatter method

[1] In a broader economic context, efficiency refers to the ability to maximize or minimize an output given specific inputs as proposed by (Kumbhakar and Lovell, 2003)

[2] The GTRE has assumes that (1) the production frontier is log-linear Cobb-Douglas, so that the poverty rate (output) is modeled as a function of subnational factors (inputs), (that is, the sectoral GDP per capita), lagged government investment, macroeconomic conditions, and idiosyncratic unobserved factors; (2) the unobserved heterogeneity and the idiosyncratic shocks are normally distributed; and (3) both the persistent and transient efficiency follow a truncated normal distribution. As shown in Jondrow et al. (1982) the distributional assumptions are necessary to separate inef-

from Cattaneo et al. (2024) to estimate the relationship between the efficiency and its potential determinants nonparametrically. In our case study, we estimate the efficiency in poverty reduction and study its relationship with the three economic sectors, unemployment, and informality. Our approach can be applied in general to any measure of efficiency, such as firm's production (Becchetti et al., 2003), energy (Filippini and Hunt, 2015), banking (Tsionas and Kumbhakar, 2014), health (Colombi et al., 2017), and insurance companies (Fenn et al., 2008).

Bolivia provides a compelling context for examining the efficiency of poverty reduction at the subnational level and understanding the factors influencing it. The regional dynamics of the country, characterized by the strengthening of the middle class through poverty-reduction initiatives and its subnational susceptibility to macroeconomic conditions, make it a promising case for such analysis. Since 2000, Bolivia has made significant progress in reducing poverty, with the rate decreasing from 64.5 percent in 2000 to 39.7 percent in 2021 (see table 1). States with higher income levels and larger populations experienced a more rapid decline, while others lagged behind significantly. This positive trend can be attributed to factors such as the increase in both labor and nonlabor income, along with a rise in the labor force participation rate among working-age individuals. Government efforts to alleviate poverty were reflected in substantial investment growth, with marked heterogeneity across states, particularly in social security, which increased nearly fourfold between 2007 and 2017. The initial decline in poverty was largely driven by favorable macroeconomic conditions, fueled by the commodities boom in the early 21st century that, through government transfers, brought significant resources to certain states. However, the subsequent decline in commodity prices, starting around 2014, led to a slowdown in the pace of progress in poverty reduction (Davalos et al., 2020), with some states being more affected than others.

Our analysis reveals that efficiency in poverty reduction is predominantly persistent rather than transient. As a result, the recalibration of poverty-alleviating policies should prioritize long-term strategies, given the limited impact of implementing effective short-run policies. Our findings also indicate if the macroeconomic conditions in Bolivia as a whole allow for a 10 percent reduction in the poverty rate, states can achieve at most an 8.2 percent reduction, and on average, they reduce it by 7.3 percent. The states demonstrating the highest efficiency in poverty reduction are Santa Cruz, La Paz, and Pando, with a technical (short-term) efficiency around 0.8 and a persistent (long-term) efficiency of 0.9. Following closely are Beni, Oruro, and Cochabamba, with values around 0.74 and 0.83, respectively.[3] In stark contrast, Chuquisaca and Potosí stand out as the least

ficiency from the idiosyncratic error. Under these assumptions, the efficiency is identified as the ratio of the observed poverty rate to the minimum feasible poverty rate. To estimate it we use a Markov Chain Monte Carlo (MCMC) sampler in a Bayesian framework. To compute the posterior distributions for the MCMC sampler, Jondrow et al. (1982) also assume a normal distribution for the location parameters and an inverse gamma for the scale parameters.

[3]Efficiency takes a value between 0 and 1. Consider the case that given some state's resources, it should be able

efficient states: both are associated with an technical efficiency of 0.58 and a persistent efficiency of 0.65. While efficiency levels across states remained relatively stable from 2001 to 2021, Potosí and Chuquisaca experienced a decline in efficiency over time. In contrast, Beni and Santa Cruz significantly increased their efficiency during the same period. The binscatter least squares regression suggests that efficiency in poverty reduction is positively associated with the size of the tertiary sector. The relationship with the primary and secondary sectors depends on their size, with efficiency being positive when these sectors are big enough. We also find that efficiency is negatively related to unemployment and informality. Accordingly, strengthening the labor market could help public investment be more effective at poverty reduction.

The remainder of this paper proceeds as follows: section 2 presents a brief literature review on poverty reduction, economic growth, and public spending efficiency. The data and methodology are presented in section 3. The key findings are reported in section 4 and section 5 concludes.

2 Poverty Reduction, Determinants, and Efficiency

The literature on the relationship between growth and poverty predominantly shows a positive relation, with certain studies diverging as to the decisive evidence of this relationship. However, such findings rely mostly on a mechanical relationship between income growth and poverty reduction rather than being derived from an empirical relationship or a structural model (Ravallion and Huppi, 1991).

Taking a closer look at growth, an important aspect that the pro-poor growth literature quite often underestimates is sectoral dynamics in general and specifically which economic sector contributes most to poverty reduction. While the majority of studies emphasize the role of the primary sector, a consensus remains elusive due to cross-country heterogeneity. Studies of several Asian countries demonstrate that the primary sector, particularly agriculture, plays a pivotal role in poverty reduction, with Ravallion and Datt (1996) and Ravallion (1999) underscoring the poverty-reducing impact of the agricultural sector compared to manufacturing. Narrowing the study context to China, Montalvo and Ravallion (2009) find that the primary sector, particularly agriculture, is the most effective in alleviating poverty. Ravallion and Datt (1999) echo these findings for India, emphasizing the agricultural sector's role, primarily in rural areas, as the driving force behind poverty reduction. In Indonesia, Bresciani and Valdés (2007) and Suryahadi et al. (2009) identify the rural

to reduce its poverty rate by 10 percent, but if its technical efficiency is 0.7, then it can only reduce its poverty rate $10\% \times 0.7 = 7\%$ at most.

agricultural sector as the most potent force in reducing poverty. Recent evidence from Ferreira et al. (2010) suggests that, in poor countries, increased agricultural productivity has a more substantial impact on poverty reduction than changes in industry or services. This is corroborated by Warr and Suphannachart (2021), who highlight that agricultural productivity growth in Thailand contributes significantly to the reduction of rural poverty. However, contrasting perspectives have been presented, with Canavire-Bacarreza et al. (2018) and Warr (1998) suggesting that the secondary sector surpasses agriculture when it comes to poverty reduction and Ferreira et al. (2010), who examine Brazil, report that the services sector has a more considerable impact than industry and agriculture on poverty reduction.

Shifting the focus to the efficiency of public spending, the existing literature predominantly has explored the impact of properly targeted public spending on economic growth and in turn on a country's ability to navigate recessions.[4] The general consensus is that economic performance can be enhanced without a proportional increase in public expenditure. Two main strands of this literature have emerged, one scrutinizing efficiency at the municipality or state level and the other doing so at the country level. At the subnational level, De Borger and Kerstens (1996) utilize data envelopment analysis (DEA) and free disposal hull (FDH) to evaluate the efficiency of local governments in Belgium, while Afonso and Fernandes (2003) find that municipalities in the region of Lisbon and Vale do Tejo in Portugal could achieve the same level of output with 39 percent fewer resources on average. On a broader scale, Bose et al. (2007), examining a panel of 30 developing countries from 1970 to 1990, suggest that while current expenditure is not significant, the share of government capital expenditure in GDP is positively associated with economic growth. Finally, Afonso et al. (2005), assessing 23 industrialized countries, conclude that the highest overall performance is linked with countries possessing smaller public sectors.

Within the literature, a specific focus has been devoted to understanding the efficiency of public spending in the context of poverty reduction. Afonso et al. (2005) reveal a connection between more-equitable income distribution and larger public sectors. This work is pertinent to our research because it explores the intricate relationship between the size of the public sector and income distribution, using the share of the poorest 40 percent of households as a proxy. Herrmann et al. (2008) conduct a qualitative analysis across 27 EU-28 countries (excluding Croatia) that illuminates considerable heterogeneity in terms of efficiency of public spending, with Finland and the Netherlands emerging as the most efficient countries. Presenting similar findings, Valls Fonayet et al. (2020) conclude that the Continental and Nordic Welfare models exhibit elevated social expenditure levels and efficiency beyond the average for the same group of countries. Conversely, Mehmood and

[4] Brini et al. (2016) conduct an extensive review of the literature on efficient public spending and its effect on economic growth.

Sadiq (2010) delve into Pakistani data spanning from 1976 to 2010 that lead the authors to the finding of a negative relationship between government expenditure and poverty.

Two notable recent studies, Rambe et al. (2022) and Ambarkhane et al. (2020), contribute further insights: the former evaluates the efficiency of pro-growth poverty reduction spending in Indonesia before and during the COVID-19 pandemic and the latter, closely aligned with our research, utilizes data envelopment analysis (DEA) to assess the efficiency of Indian states in reducing poverty, specifically considering economic growth, government expenditure, and additional macroeconomic variables. They find that states with higher economic growth exhibit greater efficiency. Our study advances this strand in the literature by disentangling permanent and transient inefficiencies through the generalized true random-effects model (GTRE). The isolation of permanent inefficiency in our approach carries two notable advantages. First, from a theoretical standpoint, estimating a model with just one inefficiency component can yield inaccurate estimates of that component, as emphasized by Tsionas and Kumbhakar (2014). Second, from an empirical standpoint discerning the extent of persistence in inefficiency makes possible more-precise public policy recommendations. If inefficiency is predominantly persistent, short-term interventions may not yield the anticipated effectiveness. Conversely, if inefficiency is largely time varying, states can prioritize short-term policies for immediate poverty reduction without needing to overhaul their poverty-reduction strategy.

3 Data and Methodology

3.1 Data

We analyze the efficiency of Bolivian states in poverty eradication using state-level data spanning from 2000 to 2021.[5] Our data set integrates economic indicators from the Instituto Nacional de Estadística (INE) and public-sector investment data from the Ministry of Finance. Covering the nine states (*departamentos*) in Bolivia, we derive variables related to poverty and employment from the household surveys. Labor informality is calculated considering both the type of production unit and the legal aspect of contract signing. Data related to gross domestic product (GDP) at the state level are sourced from the INE, while information on social programs and tax revenues is sourced from the Social and Economic Policy Analysis Unit (UDAPE). Due to INE data's being missing

[5] While the household surveys that the Bolivian government has undertaken are representative at the state level since 2011, we expand the data backwards to obtain a larger data set, though at the risk of losing representativeness. However, we test by grouping states by the three regions of the initial surveys and the results are consistent.

for 2004 and 2010, the data set comprises 180 observations, representing 9 states observed over 20 years. We address the only other missing data point, the informality rate in 2005, through multiple imputation using Amelia II (Honaker et al. (2010)).

Our data set encompasses variables such as poverty rate, sectoral GDP, government investment by area, informality, and terms of trade. GDP is categorized into primary, secondary, and tertiary sectors. Descriptive statistics include the middle-class and rich rates, as well as state populations for size computation. We identify the poor using a national poverty line defined by INE, which varies by state and year [6]

As mentioned previously, from 2000 to 2021 Bolivia made significant strides in reducing poverty. Table 1 presents the wealth distribution across income groups during this period. In 2000, 34.6 percent of Bolivians were in the middle class, while 64.5 percent were classified as poor. By 2021, the proportion of the poor had decreased by approximately 25 percentage points to 39.7 percent. Simultaneously, the middle class expanded to include almost 60 percent of the population. Key drivers of this poverty reduction include the commodity boom, labor market dynamics, and a substantial increase in government expenditure. The commodity boom from 2006 to 2014 led to increased labor demand and higher household incomes and subsequently a positive impact on poverty reduction. The expansion of low-skill sectors, such as construction, commerce, and services, resulted in heightened labor income and increased labor force participation (Davalos et al., 2020).

Table 2 reports the sectoral and total economic growth and the corresponding shares for the 2001–2021 period. The highest levels of economic growth, which occurred in the period 2006–2014, were mainly driven by the boom in the commodities market. There is a great deal of heterogeneity with regard to the most important sector for the economy. For example, in 2008 the best-performing sector was the primary, whereas in 2015 it was the tertiary and in 2016 it was the secondary. In terms of the composition of the economy, the shares of the sectors were relatively steady during the period under study. The primary sector expanded in 2008 to be almost 30 percent as a result of the commodity boom, but afterward, it slowly contracted to being 25 percent. The proportions of the secondary and tertiary sectors saw little fluctuation: the former accounted for around a quarter of the GDP and the latter around half. A rudimentary way to look for evidence of pro-poor growth is by relating column 2 in both table 1 and table 2. If growth is poverty reducing, then the poverty rate should be negatively correlated with the (lagged) growth of the GDP. If there

[6] The vulnerable middle class has incomes less than twice the poverty line, while the consolidated middle class earns between twice and ten times the poverty line. Households earning more than ten times the poverty threshold are considered rich. For our preliminary analysis, we use the four categories, but for estimation, only the definition for the poor is employed.

TABLE 1: Bolivia's Wealth Distribution (%)

		Middle Class		
Year	Poor	Vulnerable	Consolidated	Rich
2000	64.52	21.39	13.24	0.84
2001	70.46	17.78	10.94	0.81
2002	70.82	17.10	11.21	0.86
2003	61.61	22.37	15.03	0.98
2005	61.03	21.37	16.29	1.30
2006	58.41	21.85	18.64	1.09
2007	59.44	21.99	17.68	0.89
2008	56.10	27.10	15.92	0.88
2009	50.16	31.05	17.93	0.86
2011	48.05	30.46	20.90	0.59
2012	43.87	32.61	22.93	0.59
2013	39.50	33.84	25.98	0.68
2014	40.43	32.41	25.97	1.19
2015	39.66	32.85	26.65	0.84
2016	42.71	31.03	25.63	0.62
2017	39.25	31.86	28.34	0.54
2018	36.72	39.64	23.35	0.31
2019	38.84	38.29	22.47	0.42
2020	43.22	34.43	21.49	0.47
2021	39.66	36.80	21.49	0.45

Source: INE Household Surveys.

is no correlation, it is highly unlikely that there is pro-poor growth. We find that at the department level, the correlation between the (lagged) annual GDP growth and the rates of growth of the poor is -0.3651, suggesting that economic growth could have been one of the drivers of the improvement in citizens' quality of life, in particular the substantial migration of the poor into the vulnerable and consolidated middle classes.

Figure 1 illustrates the sectoral and total growth throughout the study period. Notably, the growth rate of the tertiary sector exhibited a consistent upward trajectory. Following a dip with a negative growth rate of 1.2 percent in 2003, the secondary sector maintained an annual growth rate surpassing 3 percent, peaking in 2006 as the primary driver of economic growth. The manufacturing sector was primarily responsible for this expansion, consistently contributing over 80 percent to the sector's production throughout the study period. In terms of growth variability, the primary sector experienced the most fluctuations. After reaching its pinnacle in 2008 during the commodity boom, it was characterized by annual growth rates ranging from 1.3 to 7 percent until 2017. Total GDP growth, like the tertiary sector, exhibited a steady increase, trending upward from 2005 to

TABLE 2: Sectoral Economic Growth and Shares (%)

	Growth				Share		
Year	GDP	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary
2001	1.60	1.45	0.99	1.92	25.89	21.71	52.40
2002	1.95	1.24	2.82	1.93	25.71	21.89	52.39
2003	2.70	7.22	-1.20	2.10	26.85	21.06	52.09
2004	3.62	3.80	5.10	2.92	26.90	21.36	51.74
2005	4.00	8.29	3.46	1.99	28.01	21.25	50.74
2006	4.67	4.73	8.11	3.20	28.02	21.95	50.03
2007	4.38	2.72	7.25	4.05	27.58	22.56	49.87
2008	6.07	11.71	4.49	3.66	29.04	22.22	48.73
2009	3.94	0.87	5.75	4.94	28.19	22.61	49.20
2010	3.66	1.32	3.39	5.12	27.55	22.55	49.90
2011	4.41	4.12	4.41	4.57	27.47	22.55	49.98
2012	4.39	4.52	5.32	3.90	27.51	22.75	49.74
2013	6.31	6.82	6.91	5.76	27.64	22.88	49.48
2014	4.99	4.85	4.74	5.19	27.60	22.82	49.57
2015	4.46	1.78	4.73	5.82	26.89	22.88	50.22
2016	4.28	1.33	6.51	4.84	26.14	23.37	50.49
2017	4.17	3.60	3.62	4.73	25.99	23.25	50.76
2018	4.32	2.10	5.12	5.10	25.44	23.43	51.14
2019	2.43	0.16	2.94	3.33	24.87	23.54	51.59
2020	-8.43	-5.49	-10.14	-9.07	25.67	23.10	51.23
2021	6.44	7.66	6.36	5.87	25.96	23.09	50.95

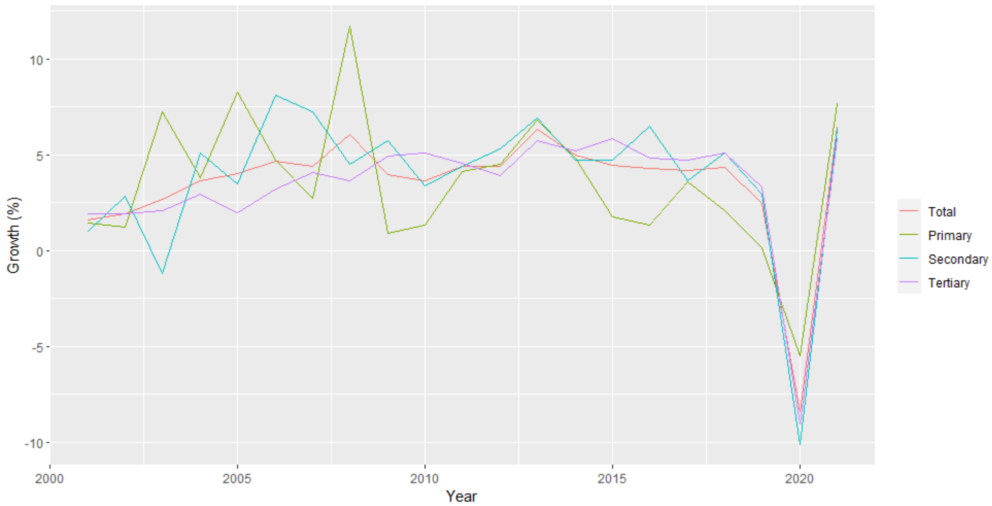
Source: INE Household Surveys.

2017. A marginal decline in growth occurred in 2019, followed by a substantial drop in 2020 due to the pervasive impact of the COVID-19 pandemic across all sectors. A modest recovery ensued in 2021.

One important source of spatial variation in poverty (and efficiency in poverty alleviation) is budget execution. The size and allocation of public investment affect poverty directly and indirectly. On the one hand, if the aid is targeted exclusively at the poor, the income distribution can be shifted, favoring the poor. On the other hand, public investment, for example in education, social security, and sanitation, can also improve the welfare of the poor (Gomanee et al., 2003).

Descriptive statistics for public investment in various sectors——productive, infrastructure, social, and social security——are provided in table 3. Notably, social security accounted for the majority of investments, followed by infrastructure spending. Despite there being significant disparities in investment between the social and the productive sectors (with investment in infrastructure in

FIGURE 1: Sectoral and Total Growth (%) 2001—21



2017 being double that in the productive sector), all categories experienced noteworthy development over the study period. Starting from 2016, amid lower economic growth and a relative increase in spending on inflexible items such as salaries, coupled with reduced investment in hydrocarbon projects, social security spending gained increasing prominence both in absolute terms and relative to other areas. From 2018 onward, every sector witnessed a substantial absolute decrease except for social security, which continued to rise until 2021. Although our study is not designed to establish causation, our model enables an assessment of whether governmental efforts in each area were associated with poverty alleviation in Bolivia.

3.2 METHODOLOGY

Following Tsionas and Kumbhakar (2014), we consider an objective variable, poverty, as a cost function. Thus, letting the poverty rate in state $i = 1, 2, \ldots, J$ at time $t = 1, 2 \ldots, T$ be defined as $P_{it} = \frac{1}{N_{it}} \sum_{i=1}^{N_{it}} I(y_i < z)$, where y_i represents income and z the poverty line, we propose that the poverty rate in state i at time t is minimized by subnational factors related to the GDP per capita ($\boldsymbol{Y}_{it}$), lagged government investment ($\boldsymbol{X}_{it-1}$), macroeconomic conditions ($\boldsymbol{Z}_{it}$), and idiosyncratic unobserved factors. Accordingly, the general model is

$$P_{it} = f(\boldsymbol{Y}_{it}, \boldsymbol{X}_{it-1}, \boldsymbol{Z}_{it}; \boldsymbol{\theta}) \times \exp\{v_{it}\} = \prod_j Y_{jit}^{s_{i,t-1}^{j}\beta_{ji}} \times \prod_m X_{mit-1}^{\gamma_m} \times \boldsymbol{Z}_{it}^{\boldsymbol{\phi}} \times \exp\{v_{it}\}, \tag{1}$$

where the location parameters are given by $\boldsymbol{\theta} = (\boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\phi})'$, v_{it} is the idiosyncratic error, j corresponds to the j-th economic sector, $s_{i,t-1}^{j} = \frac{Y_{i,t-1}^{j}}{Y_{i,t-1}}$ is the share of the j-th sector in the economy, and

TABLE 3: Public Investment by Area, 2001—21 (USD, millions)

Year	Productive	Infrastructure	Social	Social security
2001	61.3	229.0	252.8	501.0
2002	58.7	221.8	218.8	575.9
2003	43.2	227.7	163.7	808.0
2004	51.5	296.4	199.4	826.0
2005	67.2	325.7	173.4	867.6
2006	92.2	481.1	244.7	1095.1
2007	117.3	550.1	274.4	1153.0
2008	143.4	641.6	419.0	1952.0
2009	178.8	692.8	447.4	2040.4
2010	219.7	720.3	440.6	2150.5
2011	538.5	866.3	531.3	2232.2
2012	791.0	1072.7	686.1	2295.8
2013	995.2	1367.5	1032.4	2780.8
2014	1093.1	1618.3	1380.2	3317.9
2015	1315.3	1977.6	1239.1	3393.2
2016	944.8	2583.4	1138.8	3510.0
2017	823.2	2345.9	1128.8	4060.5
2018	561.4	2007.1	1392.7	4412.1
2019	450.1	1645.2	1264.8	4941.4
2020	212.9	645.8	675.3	5244.8
2021	273.7	1174.1	855.5	5344.2

Source: Ministry of Finance of Bolivia.

$f(\cdot;\cdot)$ is the production frontier. As in Tsionas and Kumbhakar (2014) we break the idiosyncratic error into the four components of unobserved heterogeneity (α_i), stochastic shock (ϵ_{it}), persistent inefficiency (η_i^+), and transient inefficiency (u_{it}^+), yielding

$$P_{it} = f(\boldsymbol{Y}_{it}, \boldsymbol{X}_{it-1}, \boldsymbol{Z}_{it}; \boldsymbol{\theta}) \times \exp\{\epsilon_{it}\} \times \exp\{\alpha_i\} \times \exp\{\eta_i^+ + u_{it}^+\}, \tag{2}$$

or equivalently

$$P_{it} = f(\boldsymbol{Y}_{it}, \boldsymbol{X}_{it-1}, \boldsymbol{Z}_{it}; \boldsymbol{\theta}) \times \exp\{\epsilon_{it} + \alpha_i\} \times TE_{it}, \tag{3}$$

where α_i captures unobserved factors of state i that affect the poverty rate and are time invariant. The technical efficiency (TE_{it}) captures the factors that can be controlled by the state, while ϵ_{it} captures those effects affecting the poverty rate that cannot be controlled by the state (Hjalmarsson et al., 1996). $TE_{it} := \exp\{\eta_i^+ + u_{it}^+\}$ is the technical (in)efficiency, which arises from the fact that states are not fully efficient at reducing poverty (parallel to firms' incurring higher costs than they should, given their inputs). The u_{it}^+ is the short-run or transient component, which is associated with the state's contingent inability to reduce poverty. This could be due to the misallocation of resources of a given program. In Bolivia, the increase in income generated by the commodity super cycle led to the implementation of a series of social cash transfer programs, which have been mentioned as drivers of poverty reduction. However, scholars have found that the effect on poverty and inequality was meager. Chacon and Valencia (2018), for example, on the basis of a study of the distributive efficiency of three transfer programs (Bono Juancito Pinto, Renta Dignidad, and Bono Juana Azurduy), estimate that 21 percent of the beneficiaries were not the most needy. These authors conclude that the vouchers were not responsible for the reduction of poverty in Bolivia; instead, this effect occurred due to the increase in the labor income of the neediest families in the country, given that at the time of the study, approximately 85 percent of total household income was from labor income and not from transfers.

Moving from the short to the long term, η_i^+ is the long-run or persistent component, which evaluates the persistent inefficiency of a state's effort to reduce poverty. This could encompass, for example, lack of capacities, especially at the territorial level. Bolivia as a country has been improving its capacities in the last decades and lowering its poverty levels. Even so, there is a substantial amount of work to be done and one of the biggest risks is that poverty reduction is not very sustainable and vulnerable to negative economic shocks. This is a significant consideration, because (monetary) poverty, as mentioned above, depends on income, with 85 percent of family income being from work, most of which (approximately 75 percent) is informal.

To illustrate why technical efficiency is considered a valid measure of efficiency, we rewrite equation (3) as

$$TE_{it} = \frac{P_{it}}{f(\boldsymbol{Y}_{it}, \boldsymbol{X}_{it-1}, \boldsymbol{Z}_{it}; \boldsymbol{\theta}) \times \exp\{\epsilon_{it} + \alpha_i\}},$$

so that technical efficiency is the ratio of the observed poverty rate to the minimum feasible poverty rate. This way, the poverty rate is minimal only if the technical efficiency equals 1. If it is less than 1, the technical efficiency provides a measure of the shortfall of observed output (poverty rate) from the minimum feasible output (Kumbhakar and Lovell, 2003).

To obtain our estimable equation, we take logs to eq. (2) and let ($y^j_{it} = log(Y_{jit})$, $x^m_{it} = log(x_{mit})$, $\boldsymbol{z}_{it} = log(\boldsymbol{Z}_{it})$, $p_{it} = log(P_{it})$), which yields

$$p_{it} = \sum_j y^j_{it} s^j_{i,t-1} \beta_{ji} + \sum_m x^m_{it-1} \gamma_m + \boldsymbol{z}'_{it} \boldsymbol{\phi} + \alpha_i + \eta^+_i + u^+_{it} + \epsilon_{it}. \tag{4}$$

Setting $\eta^+_i = u^+_{it} = 0$ and taking differences to eq. (4) boils down to the specification in Ferreira et al. (2010) and Canavire-Bacarreza et al. (2018). Accordingly, our general model coincides with the customary approach when states are assumed to be fully efficient at poverty reduction. Nonetheless, such an assumption is not restrictive, because the main aim in these two papers is to assess how poverty reducing each sector is relative to the others. In contrast to Ferreira et al. (2010) and Canavire-Bacarreza et al. (2018), we assume that sectoral growth elasticities are constant across states, that is, $\beta_{ji} = \beta_j$ for every i. We impose this restriction because we require the estimation of efficiency by year and time period for every state (which implies the computing of $N \times (T + 1)$ additional parameters). Given that our objective is predictive rather than causal, we do not consider such an assumption very restrictive.

Our approach diverges from the mainstream nonparametric approach employed in the literature on the efficiency of public spending. Efficiency is commonly assessed by means of DEA or FDH. The rationale behind this is the flexibility provided by both approaches, given that they are nonparametric. Nonetheless, in both models the likelihood of the observational units being found to be efficient increases with the number of inputs that are incorporated. The reason is that both DEA and FDH optimize the weights of the "niche" inputs (Chen et al., 2015). In our analysis we also incorporate sectoral growth and macroeconomic variables, increasing the dimensions of the inputs substantially. Accordingly, even though DEA and FDH offer a nonparametric approach, as opposed to our model in eq. (4), they have limited capability to incorporate numerous variables without overestimating efficiency. We use the GTRE so that we are able to make use of a rich set of variables to compute efficiency while being able to analyze the degree of association between the inputs and poverty reduction.

We estimate equation (4) by means of a GTRE. This model coincides with the Bayesian longitudinal model, which tackles the endogeneity issues arising from the fixed effects without the need for a transformation of the variables or reliance on their independence from the covariates. Moreover, it only requires that a set of units are observed at different moments in time, so the panel need not be balanced or equidistant.

We now turn to the specification of eq. (4). Our dependent variable is the (log) poverty rate by state. The GDP ($\boldsymbol{Y}_{it}$) is broken into primary, secondary, and tertiary sectors. We incorporate the weighting by share from Ravallion and Datt (1996), Ferreira et al. (2010), and Canavire-Bacarreza et al. (2018), so that the $j-th$ economic sector is weighted by its share $s^J_{i,t-1} = \frac{Y^J_{i,t-1}}{Y_{i,t-1}}$. Government investment $(\boldsymbol{X}_{it})$ is differentiated by area: productive, infrastructure, social, and social security. Macroeconomic conditions incorporate (1) terms of trade, due to the fall in the price of commodities between 2013 and 2017 and the corresponding commodity boom; (2) employment rate, to control for the increase in the labor force participation rate of working-age people;, and (3) the informality rate, to capture Bolivian labor market dynamics.[7] This is due to the fact that Bolivia has one of the highest levels of informal work in the world (higher than 80 percent in the period under study). In our study, we consider informal workers to be those who do not participate in social security systems.

For ease of notation, consider the compact representation of eq. (4)

$$p_{it} = \boldsymbol{w}'_{it}\boldsymbol{\theta} + \alpha_i + \eta^+_i + u^+_{it} + \epsilon_{it}, \tag{5}$$

where $\boldsymbol{w}_{it} = [\boldsymbol{S}'_{t-1}\boldsymbol{y}'_{it}, \boldsymbol{x}'_{it-1}, \boldsymbol{z}'_{it}]'$, and the j-th entry of $\boldsymbol{S}_{t-1}$ is given by the shares $s^j_{i,t-1}$. We use the same prior distributions (so that we have the same posterior distributions) as in Tsionas and Kumbhakar (2014) for the random elements in eq. (5):

$$\alpha_i \sim \mathcal{N}(0, \sigma^2_\alpha), \quad \eta^+_i \sim \mathcal{N}^+(0, \sigma^2_\eta), \quad u^+_{it} \sim \mathcal{N}^+(0, \sigma^2_u), \quad \epsilon_{it} \sim \mathcal{N}(0, \sigma^2_\epsilon), \tag{6}$$

where $\mathcal{N}$ and $\mathcal{N}^+$ stand for normal and half-normal distributions. For the scale parameters of the inefficiency components, we make the corrections suggested by Makieła (2017). This way, the priors are $\sigma^2_u \sim IG(v_{0u}/2, 2v_{0u}\log^2(r^*_u)/2)$ and $\sigma^2_\eta \sim IG(v_{0\eta}/2, 2v_{0\eta}\log^2(r^*_\eta)/2)$, where the prior medians of the transient and persistent one-sided errors are equal to $r^*_u = 0.85$ and $r^*_\eta = 0.70$, respectively, and $v_{0u} = v_{0\eta} = 10$. This correction leads to better behavior of the Gibbs sampling in the presence of noisy data sets and also enables us to make simpler (less-informative) assumptions regarding prior transient and persistent inefficiency distribution (Makieła, 2017).

By defining the augmented vector as $\boldsymbol{\Theta} = (\boldsymbol{\theta}', \sigma^2_\alpha, \sigma^2_\epsilon, \sigma^2_\eta, \sigma^2_u, u^+_{it}, \eta^+_i)$ and using data augmenting (Tanner and Wong, 1987), the model in eq. (5) along with the assumptions in eq. (6) yields a

[7]We also include a trend in the specification.

likelihood of the form

$$
\begin{aligned}
f(\boldsymbol{p}|\boldsymbol{w},\boldsymbol{\Theta}) = \prod_{i=1}^{N} \exp\bigg\{ -\frac{1}{2\sigma_\epsilon^2}\big(\boldsymbol{p}_i - \boldsymbol{w}_i'\boldsymbol{\theta} - \alpha_i \boldsymbol{i}_T - \boldsymbol{u}_{it}^+ - \eta_i^+\boldsymbol{i}_T\big)'\big(\boldsymbol{p}_i - \boldsymbol{w}_i'\boldsymbol{\theta} - \alpha_i \boldsymbol{i}_T - \boldsymbol{u}_{it}^+ - \eta_i^+\boldsymbol{i}_T\big)\bigg\} \\
\times I(\boldsymbol{u}_{it}^+ < 0)\left(\frac{2}{\pi}\right)^{-\frac{T}{2}} (\sigma_u^2)^{-\frac{T}{2}} \exp\bigg\{-\frac{1}{2\sigma_u^2}\boldsymbol{u}_{it}^{+'}\boldsymbol{u}_{it}^+\bigg\} \\
\times I(\eta_i^+ < 0)\left(\frac{2}{\pi}\right)^{-\frac{T}{2}} (\sigma_\eta^2)^{-\frac{T}{2}} \exp\bigg\{-\frac{1}{2\sigma_\eta^2}\eta_i^{+'}\eta_i^+\bigg\}.
\end{aligned} \tag{7}
$$

Given the likelihood in eq. (7) and the prior distribution, we compute the posterior distributions with the Bayes rule, that is,

$$
\pi(\Theta|\boldsymbol{w},\boldsymbol{p}) = \frac{f(\boldsymbol{p}|\boldsymbol{\Theta},\boldsymbol{w}) \times \pi(\Theta|\boldsymbol{p},\boldsymbol{w})}{\pi(\boldsymbol{w},\boldsymbol{p})}.
$$

The resulting posterior distributions are the same as in Tsionas and Kumbhakar (2014), except for those for the scale parameters of the inefficiencies, which have the following form:

$$
\sigma_u^2|\boldsymbol{\Theta}_{-\sigma_u}, \boldsymbol{y}, \boldsymbol{X} \sim IG\bigg(\frac{(N\times T) + v_{0u}}{2}, \frac{\boldsymbol{u}^{+\top}\boldsymbol{u}^+ + 2v_{0u}\log^2(r_u^*)}{2}\bigg),
$$

and

$$
\sigma_\eta^2|\Theta_{-\sigma_\eta}, \boldsymbol{y}, \boldsymbol{X} \sim IG\bigg(\frac{N + v_{0\eta}}{2}, \frac{\boldsymbol{\eta}^{+\top}\boldsymbol{\eta}^+ + 2v_{0\eta}\log^2(r_\eta^*)}{2}\bigg).
$$

To estimate the inefficiency, we obtain draws from the posterior distributions of all the parameters in Θ using a MCMC sampler. In the cost-minimization framework corresponding to equation (1), efficiency is measured by technical efficiency, which in our case takes the form of $\mathbb{E}\left[\exp\left\{-u_{it}^+ - \eta_i^+\right\}\right]$, and by persistent efficiency, $\mathbb{E}\left[\exp\left\{-\eta_i^+\right\}\right]$. Performing the MCMC sampler of our model allows us to estimate such quantities. Let $u_{it}^{+(s)}$ and $\eta_i^{+(s)}$ be the draws from the conditional posterior distributions of the transient and persistent efficiencies for the s-th iteration of an MCMC scheme. Then, the posterior estimate of technical efficiency is

$$
\frac{1}{S}\sum_{s=1}^{S} \exp\left\{-u_{it}^{+(s)} - \eta_i^{+(s)}\right\}.
$$

In a fully efficient state $u_{it}^+ = \eta_i^+ = 0$, so that the last display equals 1. On the other hand, as both inefficiency components grow, the efficiency estimate approaches 0.

The persistent efficiency in poverty reduction is estimated as

$$\frac{1}{S}\sum_{s=1}^{S}\exp\left\{-\eta_i^{+(s)}\right\}.$$

As we have S draws, we can perform inference on the estimates for persistent efficiencies. In particular, we compute the highest posterior density intervals (HPDI) corresponding to 95 percent of the mass of the posterior, excluding both tails, which is “comparable” with the frequentist confidence intervals at the 95 percent confidence level. The HDPI containing 1 implies that if a state is fully efficient in a given year ($u_{it}^{+} = 0$), it can attain the minimum poverty rate reduction possible, given its macroeconomic conditions. If 1 does not belong to the HDPI, attaining the minimum poverty rate reduction is not feasible even with maximal efficiency in year ($u_{it}^{+} = 0$). Accordingly, states requiring structural interventions to efficiently alleviate poverty can be targeted with upper bounds for persistent efficiency far from 1.

4 Results

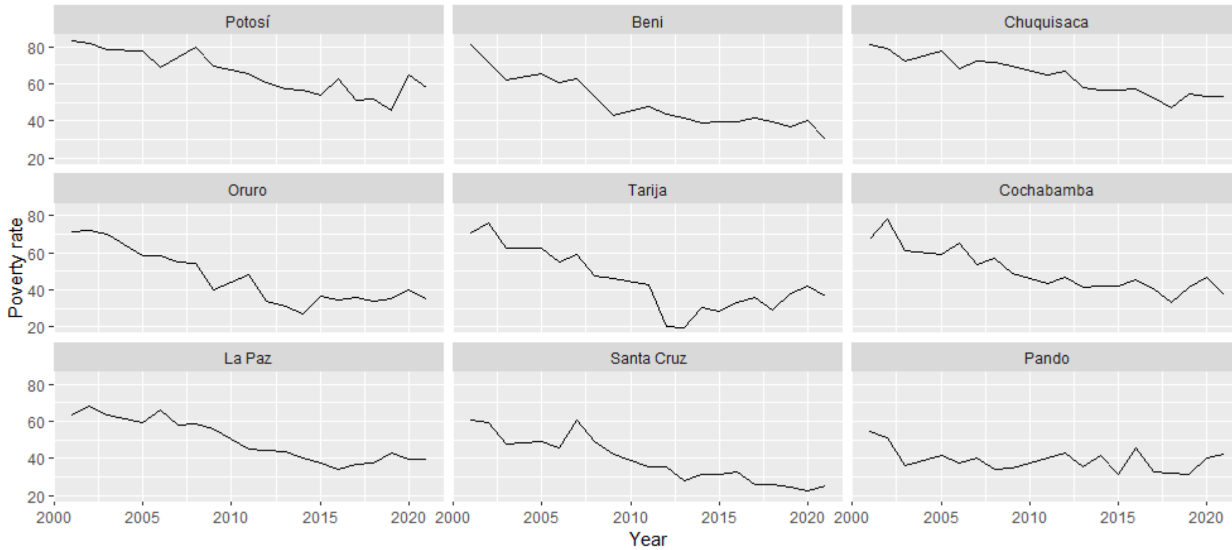
4.1 Unconditional Analysis

Before delving into the discussion of the effects of efficiency and its determinants, we conduct an unconditional analysis to examine the overall decline in the poverty rate across Bolivian states during the study period. Figure 2 portrays the evolution of the poverty rate from 2001 to 2021.[8] There is a general reduction in poverty rates, yet this phenomenon is characterized by considerable heterogeneity across states.

In 2001, Potosí, Beni, and Chuquisaca exhibited similarly high poverty rates (83.1, 81.5, and 81.0 percent, respectively). However, by 2021, Beni achieved a rate of 30.0 percent, while Potosí and Chuquisaca recorded rates of 57.8 and 53.3 percent, respectively. Oruro, Tarija, and Cochabamba all had poverty rates of approximately 70 percent in 2001 and experienced comparable declines until 2009. Subsequently, Tarija witnessed a remarkable reduction, reaching a low of 20 percent in 2013, only to see an increase thereafter, settling at 36.6 percent in 2021. In contrast, Oruro and Cochabamba observed a steady, albeit modest, decrease in the subsequent years of the study period. La Paz, Santa Cruz, and Pando had the lowest poverty rates in 2001 and moreover the

[8] We initiate reporting the poverty rate in 2001, aligning with the first year utilized for estimation, as lagged public investment is employed.

FIGURE 2: Poverty Rate Evolution 2001—21



first two, along with Chuquisaca, were the only states that did not witness an increase in poverty levels in 2020 amid the COVID-19 pandemic. Furthermore, Santa Cruz experienced a substantial drop in its poverty rate after 2007, which went from 60.7 to 25 percent in 2021. Remarkably, Santa Cruz had the second-highest poverty rate in 2001 and finished the study period in 2021 with the lowest rate.

4.2 CONDITIONAL ANALYSIS

To estimate the efficiency we obtain draws from the posterior distributions implied by equation (7) for each parameter. To do so, we perform Gibbs sampling, a MCMC algorithm in which the posterior distributions have analytical solutions.[9]

For the Gibbs sampler, we obtain posterior chains of dimension 2,500. We perform 20,000 iterations, with a burn-in period of 10,000 and a thinning parameter set to 4. A thinning parameter of value k implies that only every k-th sampled value is retained, where k is the approximate lag at which there is a lack of autocorrelation in the chain (Greenberg, 2008). Our model enables marginal analysis and the estimation of persistent efficiencies. While our primary focus is on computing state-level efficiency, we also present results for the regression coefficients. Similar to frequentist inference, the significance of Bayesian estimates at a given significance level depends on the HPDI not passing through 0. Despite the data's being at the state level, results can be

[9]This means that the distributions are known, for example, being normal or inverse gamma.

TABLE 4: Regression Results

	log(Poverty Rate)
Primary	-0.184
	[-0.461, 0.056]
Secondary	-1.825***
	[-3.019, -0.381]
Tertiary	0.139
	[-0.301, 0.561]
Productive sectors	-0.065***
	[-0.103, -0.025]
Infrastructure	0.063***
	[0.019, 0.102]
Social investment	0.014
	[-0.051, 0.085]
Social security	-0.005
	[-0.015, 0.004]
Terms of trade	0.059
	[-0.056, 0.158]
Informality	1.256***
	[0.670, 1.797]
Unemployment	0.079***
	[0.029, 0.133]
Trend	-0.019***
	[-0.025, -0.012]
Constant	-2.589*
	[-5.405, 0.194]
N	171

Note: HPDI of 95 percent in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Authors' calculations.

interpreted at the country level (Ravallion and Chen, 1999), analogous to having data at the country level and making an inference at the aggregate level, as demonstrated in Adams (2004). We restrict our marginal analysis to associations with the poverty rate.

Table 4 presents the results for the location parameters. We observe that only the secondary sector is associated with lower levels of poverty. These findings align with Canavire-Bacarreza et al. (2018) and Warr (1998), who conclude that the secondary sector contributes to poverty reduction. Additionally, we find that high investment in productive sectors is linked to lower poverty levels, though this association does not hold for high investment in infrastructure. Social investment and investment in social security appear not to be associated with poverty rates. Concerning the labor market, both unemployment and informality rates are positively associated with higher poverty levels. Given that both variables are in the same units, we find that the effect of informality seems to be more crucial than that of unemployment in poverty reduction.

In table 5, we present the results for average technical and persistent efficiency. [10] Column

[10] These results remain robust when including year dummies instead of a time trend and excluding the 2020–21 period due to the COVID-19 pandemic. Both are available upon request.

TABLE 5: Average Technical and Persistent Efficiency in Poverty Reduction

State	Technical	Transient	Persistent		
			Mean	Lower Bound	Upper Bound
Chuquisaca	61.1	7.4	68.6	57.9	78.4
Potosí	62.7	7.1	69.8	58.1	80.3
Tarija	69.8	9.7	79.5	64.0	94.5
Cochabamba	72.2	8.4	80.6	68.2	92.4
Oruro	74.1	9.0	83.2	71.3	94.6
Beni	77.1	8.8	85.9	73.3	98.9
Pando	79.3	9.5	88.8	76.1	100.0
Santa Cruz	80.0	9.1	89.0	75.8	100.0
La Paz	82.8	8.9	91.7	79.4	100.0

Technical efficiency is estimated as $\hat{\mathbb{E}}\left[\exp\left\{-\eta_i^+ - \overline{u}_{it}\right\}\right]$, transient efficiency as $\hat{\mathbb{E}}\left[\exp\left\{-\eta_i^+\right\}\right]$ - $\hat{\mathbb{E}}\left[\exp\left\{-\eta_i^+ - \overline{u}_{it}\right\}\right]$, and persistent efficiency as $\hat{\mathbb{E}}\left[\exp\left\{-\eta_i^+\right\}\right]$. The lower and upper bounds for the persistent efficiency are calculated with the HDPIs.

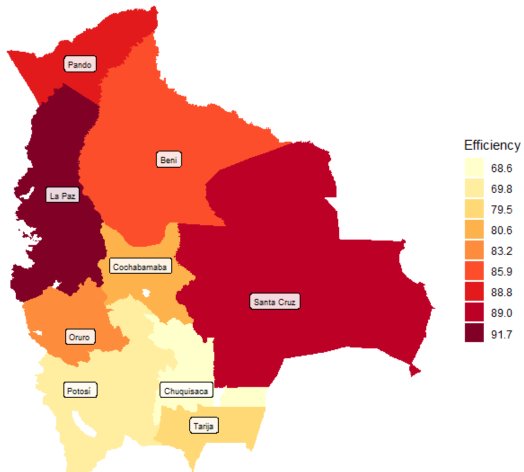
3 of table 5 indicates the estimate of persistent efficiency for the poverty reduction that a specific state can achieve, considering its macroeconomic conditions and assuming full efficiency in a given period. For instance, if state j's macroeconomic conditions in year t allow it to reduce poverty by 10 percent, and $\hat{\mathbb{E}}\left[\exp\left\{-\eta_j^+\right\}\right]$=0.7, then it can achieve a maximum reduction of $10\% \times 0.7 = 7\%$. This means that even if state j is fully efficient in allocating resources to reduce poverty in year t (so that $u_{jt}^+ = 0$), it can only achieve a fraction of the intended reduction due to efficiency constraints. Column 1 of table 5 displays the average technical efficiency, obtained by averaging the state's efficiency over the years.[11] We find that the least-efficient states were Chuquisaca and Potosí. As per figure 2, these two states, along with Beni, initially had the highest poverty rate levels but achieved much lower reductions. Both states could have reduced their poverty rates by around 40 percent more (100 to 61.1 percent and 100 to 62.7 percent, respectively) on average, given their macroeconomic conditions. Following them, the least-efficient state was Tarija, which, as mentioned earlier, experienced an increase in its poverty rate from 2013 onward. Next were Cochabamba and Oruro, which steadily decreased poverty in the study period. These two states achieved reductions of, on average, 72 and 74 percent, respectively, of the poverty rate they could. Despite reducing the poverty rate from 81.5 to 30 percent, Beni ranked fourth from the top in terms of efficiency, just behind Pando, which did not see a significant reduction in poverty levels. We find that La Paz and Santa Cruz were the most efficient states, with very similar efficiency levels as Pando.

[11] Importantly, our methodology is independent of the poverty rate level; it only indicates that if a state's resources allow it to reduce its poverty rate by, say, 10 percent, then, due to efficiency constraints, only a fraction of that reduction can actually be achieved.

Our results indicate that for every state persistent efficiency accounts for most of the effect, with short-run efficiency contributing only around 8.65 percent (the average of column 2 in table 5). This suggests that without structural changes in poverty-alleviating policies, poverty levels will not efficiently decrease over time. Implementing short-term effective policies only results in a modest improvement in welfare. As inefficiency captures every factor under the state's control that impedes it from reducing poverty, our results suggest that both short-term poverty-alleviating policies and every other short-term policy with a poverty spillover have a negligible effect.

As shown in table 5, both Potosí and Chuquisaca are far from achieving full efficiency, as the upper bounds for both are considerably below 1. For Tarija, Cochabamba, and Oruro, the upper bound is close to 100 percent, indicating that despite not reaching full efficiency in a given period, they could likely be close to full efficiency. For Pando, La Paz, and Santa Cruz, even though the point estimates suggest full efficiency was not realized, the HPDI of the persistent efficiency includes 1, implying that it is likely these states could achieve 100 percent of the poverty reduction allowed by their macroeconomic conditions. On average, the persistent and technical efficiency are 82 and 73 percent, respectively. This implies that if the macroeconomic conditions in Bolivia as a whole allow for a 10 percent reduction in the poverty rate, states can achieve at most an 8.2 percent reduction, and on average, they reduced it by 7.3 percent. Figure 3 illustrates the persistent efficiency values presented in column 3 of table 5. It reveals spatial patterns regarding inefficiency, with the most inefficient states in terms of poverty reduction being located in the southernmost part of Bolivia. This aligns with the historical poverty levels of Chuquisaca and Potosí, which have been the poorest regions in the country. For instance, data from 2021 indicate that the proportion of people in extreme poverty in these regions was three times the proportion in La Paz and ten times the proportion in Santa Cruz (INE, 2022). These high poverty levels may be related to the states' low management capacities. Additionally, these regions are abundant in natural resources, suggesting that the resource curse might play a role. Finally, the remoteness of these areas from the center of power (La Paz), in a country where geography makes certain regions especially inaccessible, limits their access to poverty-alleviating policies and infrastructure projects intended to improve quality of life (roads, water, electricity). Border and remote cities in Bolivia are often the last to receive attention from the government, exacerbating the challenges they face. The results for Potosí and Chuquisaca show that not only are they poor and inefficient regions, but there is no evidence of any convergence in efficiency over the last 20 years (figure 4). This could indicate that regions where there is a predominance of natural resources require specific policies to make poverty reduction more efficient. For example, these regions have a much more developed primary sector, which does not have as significant an effect on efficiency as the tertiary sector. However, policies to generate an economic transformation within this primary sector could be designed and

FIGURE 3: Average Persistent Efficiency in Poverty Reduction



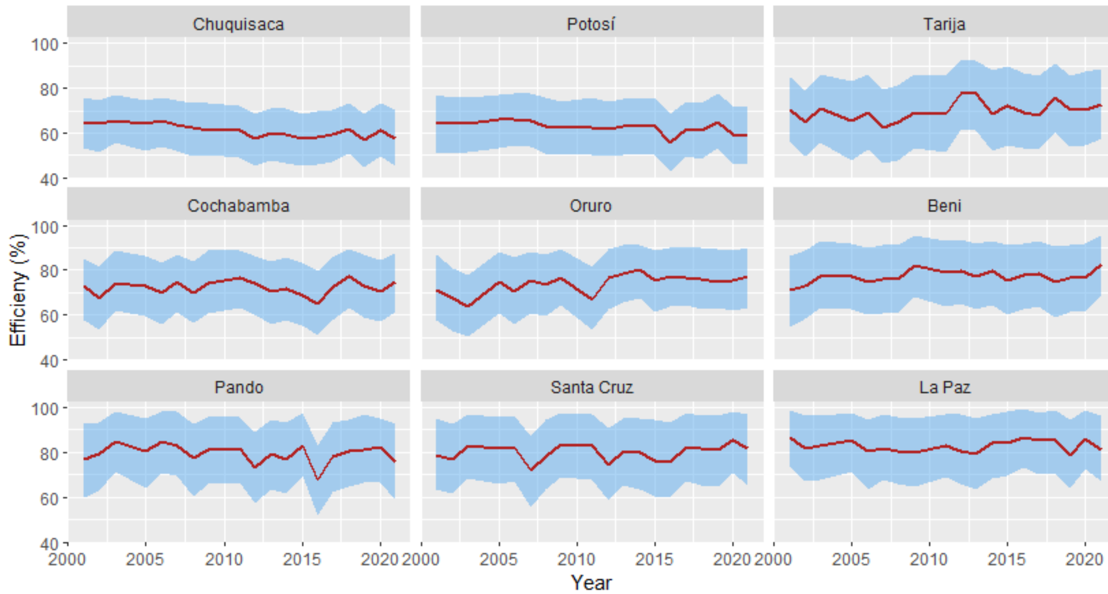
implemented, without implying a lower efficiency compared to regions where the tertiary sector is developed.

In figure 4 we present the evolution of efficiency by state from 2001 to 2021. Notably, both Potosí and Chuquisaca exhibited a decline in efficiency over time, while Tarija, Cochabamba, and Oruro experienced modest increases in their efficiency levels. Beni, the state with the highest poverty reduction during the study period, substantially enhanced its efficiency, which rose from 71 to 82 percent. Pando's efficiency fluctuated around 80 percent, experiencing a decrease in the last year of the period that dropped its efficiency level to 75 percent. La Paz witnessed a decline from 87 to 82 percent from 2001 to 2021. Conversely, Santa Cruz started with an efficiency of 79 percent and ended up with a value of 82 percent. Figure 4 reveals the lack of a consistent pattern among states becoming more or less efficient. Chuquisaca, Potosí, and La Paz became relatively less efficient from 2001 to 2021, with their efficiency levels dropping by 6.9, 5.3, and 5.5 percent, respectively. Pando saw a relatively minor decline of 1.2 percent. In contrast, Cochabamba, Tarija, and Santa Cruz experienced efficiency gains of 2.0, 2.4, and 3 percent, respectively. Notably, Oruro and Beni became substantially more efficient, with their efficiency levels rising by 5.7 and 10.9, respectively. A key takeaway from figure 4 is that even if every Bolivian state had reduced their poverty levels in the study period, it would not necessarily mean they had become more efficient in doing so. Significantly, only Oruro and Beni demonstrated improvements in their efficiency levels.

Moving on to figure 5, it reports the sample correlations of the control variables and the estimated mean efficiency with the (log) poverty rate.[12] Among these variables, efficiency stands out

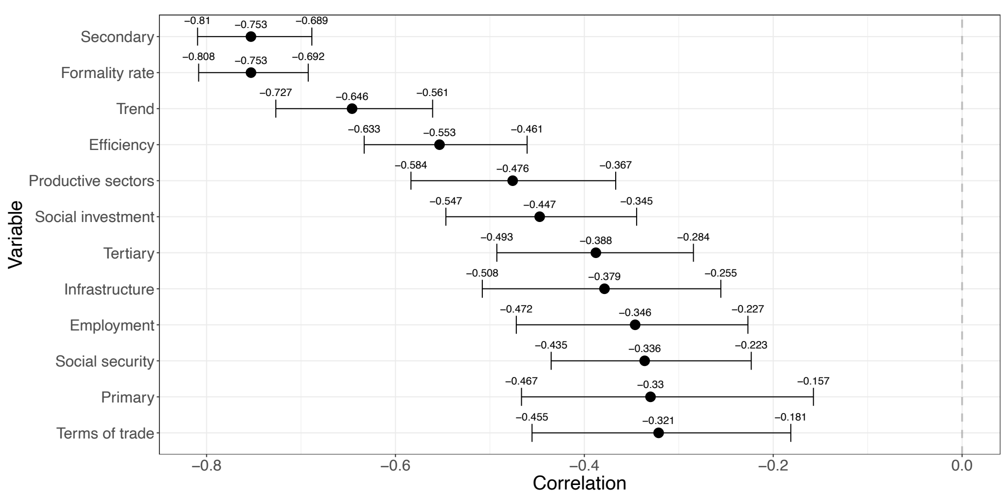
[12]For illustration purposes, we redefine informality as formality and unemployment as employment, aligning all variables to have the same sign.

FIGURE 4: Evolution of Efficiency by State, 2001—21



as one of the three with the strongest associations with the poverty rate, despite secondary sector and informality rate correlations being slightly stronger. The correlation of -0.553 indicates that disentangling the main drivers of poverty-reduction efficiency is worthwhile for effective poverty alleviation.

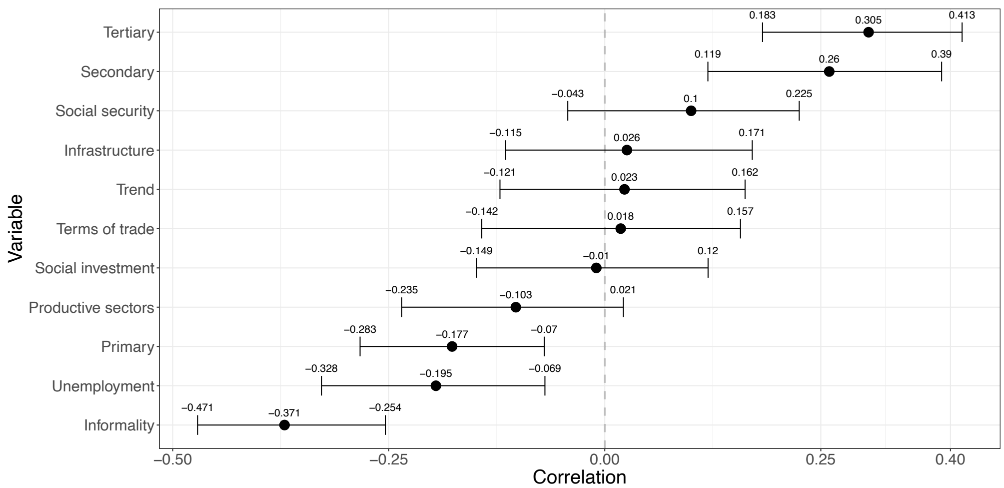
FIGURE 5: Correlations with (Log) Poverty Rate



Note: Confidence intervals of 95 percent are computed with 1,000 bootstrap samples.

To further investigate the main drivers of efficiency, we compute the sample correlations of the control variables with the estimated mean efficiency in figure 6. While this exploration is not causal, it serves as an initial step toward understanding factors associated with efficiency in poverty

FIGURE 6: Correlations with Efficiency



Note: Confidence intervals of 95 percent are computed with 1,000 bootstrap samples.

reduction. Figure 6 illustrates that the variable with the strongest association is informality; higher informality levels are correlated with lower efficiency. Bolivia faces significant challenges in this regard, because it has the highest rate of labor informality in Latin America, with more than 80 percent of workers engaged in informal employment (ILO, 2023). The high level of business informality, where inefficient companies can compete on equal terms with formal companies by evading tax responsibilities, can negatively impact the entire economy. Additionally, states where the secondary and tertiary sectors are more prominent tend to be more efficient in poverty reduction, which is potentially linked to varying productivity levels among economic sectors.

States with a primary sector focus tend to be less efficient, which is likely associated with a higher likelihood of informality, given that the primary sector often exhibits the highest informality levels. Moreover, higher levels of public investment are not necessarily associated with increased efficiency, as shown in figure 6. None of the areas of public investment displayed a correlation significantly different from 0, suggesting that proper resource allocation might be more efficient than simply increasing investment amounts. Figure 6 also indicates that higher unemployment levels are associated with lower efficiency. By regressing mean efficiency on the variable in Figure 6 (and a constant), we find that the R^2 is 0.44, suggesting that the macroeconomic conditions in our model explain almost half of the variation in efficiency. Identifying the main drivers of efficiency in poverty alleviation and understanding factors that contribute to the remaining unexplained variation could be directions for future research.

Furthermore, the information gleaned from this analysis provides insights into how public policy could be most effective. Despite the correlation nature of this exercise, it allows for a more informed exploration of the possibility of enhancing public policies aimed at reducing informality. Marginal changes based on these indicators might yield broad results in terms of efficiency in resource use, poverty reduction, and fiscal improvement. This approach could marginally affect individuals reliant on informal employment or business practices for their livelihoods. As depicted in figure 6, the variables associated with efficiency in poverty reduction are the three economic sectors, unemployment, and informality. The remaining variables do not exhibit statistical significance. Consequently, these five variables emerge as potential determinants of efficiency. To delve deeper into their relationships, we perform binscatter least squares regression with the semiparametric approach proposed by Cattaneo et al. (2024). Our object of interest is $\mathbb{E}\left[\eta_{it}|x_{it}, \boldsymbol{w}it\right]$, where xit represents one of the five potential determinants and $\boldsymbol{w}_{it}$ denotes a set of controls. This approach allows us to estimate an additively separable semilinear model and uncover the underlying relationship between efficiency and its potential drivers.

$$\eta_{it} = \mu(x_{it}) + \boldsymbol{w}_{it}'\gamma + \epsilon_{it}, \quad \mathbb{E}[\epsilon_{it}|x_{it}, \boldsymbol{w}_{it}] = 0, \tag{8}$$

where x_{it} is each of the five potential determinants, $\boldsymbol{w}_{it}$ denotes the same set of controls as in eq. (5), and ϵ_{it} is the error term. To estimate equation (8) we use the covariate-adjusted least-squares extended binscatter estimator proposed by Cattaneo et al. (2024), defined as

$$\hat{\mu}(x) = \hat{b}(x)'\hat{\beta}, \quad \begin{pmatrix} \hat{\beta} \\ \hat{\gamma} \end{pmatrix} = \text{arg min}_{\beta,\gamma} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(\eta_{it} - \hat{b}(x_{it})'\beta - \boldsymbol{w}_{it}'\gamma\right)^2,$$

where $\hat{b}(x) = \left[1_{\hat{B}_1}, ..., 1_{\hat{B}_j}\right]$ is the canonical binscatter basis given by the J-dimensional vector of orthogonal indicator variables, and

$$\hat{B}_j = \begin{cases} [x_{(1)}, x_{\lfloor n/J \rfloor}) & \text{if } j = 1 \\ [x_{\lfloor n(j-1)/J \rfloor}, x_{\lfloor nj/J \rfloor}) & \text{if } j = 2, 3, .., J-1 \\ [x_{\lfloor n(j-1)/J \rfloor}, x_{\lfloor n \rfloor}) & \text{if } j = J \end{cases},$$

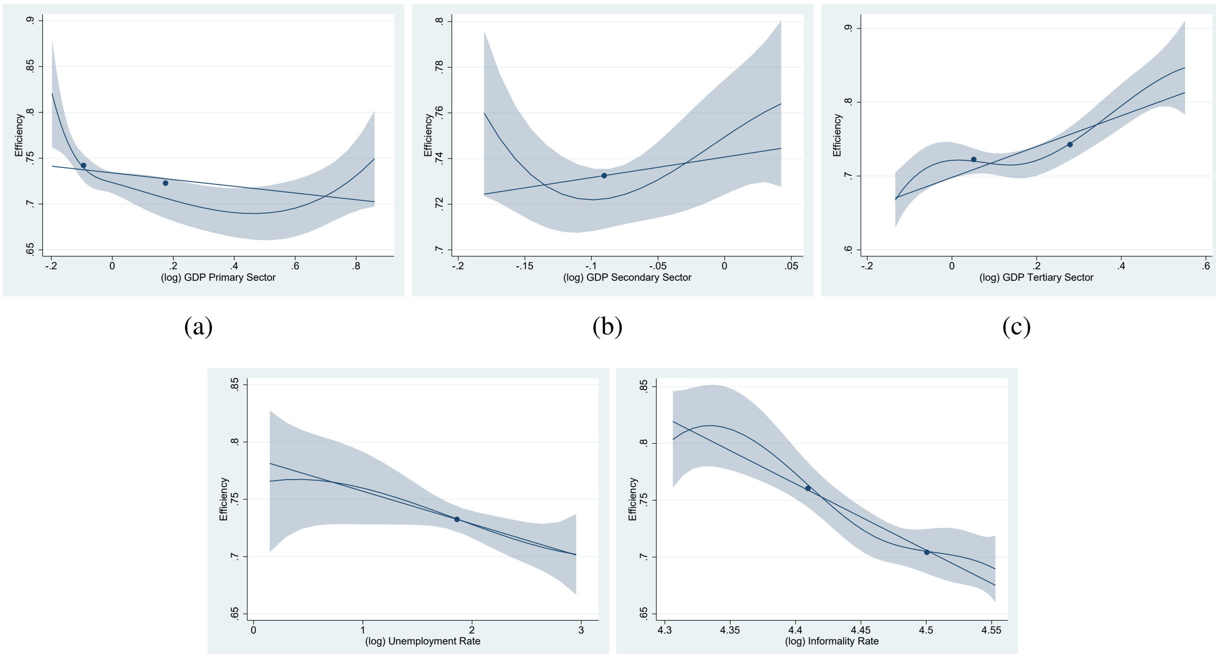
where $x_{(i)}$ the i-th order statistic of the sample $(x_1, ..., x_n)$ and $\lfloor \cdot \rfloor$ denotes the floor operator. The customary approach is to consider the number of bins J to be fixed, which is usually set to $J = 20$. However, Cattaneo et al. (2024) propose an integrated mean squared error expansion and use this to select J, which makes their proposal even more flexible and robust, because the method of setting J is data driven.

The rationale behind $\hat{\mu}(x) = \hat{b}(x)'\hat{\beta}$ is to approximate the unknown function $\mu(x)$ using a cubic B-spline. B-splines are functions constructed piecewise from cubic polynomials that are known for their flexibility in modeling nonlinear relationships. In our context, employing B-splines allows us to estimate the conditional mean of efficiency, given the five variables of interest and controlling for covariates.

The estimation results are succinctly presented in the binscatters in figure 7. Each panel in the figure displays two lines: (1) a linear fit corresponding to ordinary least squares (OLS) and (2) a cubic B-spline. Notably, panel c suggests a positive (approximately linear) relationship between efficiency in poverty reduction and the size of the tertiary sector. Conversely, the relationship with the primary and secondary sectors, as depicted in panels a and b, is highly nonlinear. Specifically, we observe that the size of these sectors is positively associated with efficiency only when the sectors reach a significant scale. Modest growth in small sectors does not lead to increased efficiency. Moreover, we find that the inflection point (where the curvature changes sign) for the primary sector is situated almost at the tail of the empirical distribution, while for the secondary sector, it is located to the left of the median. This implies that the primary sector must be substantially developed compared to the secondary sector in order to exhibit a positive relationship with efficiency in poverty reduction. This observation aligns with the low productivity level in the primary sector. Bolivia, in this regard, follows a similar pattern due to its high level of informality, which is indicative of low economic efficiency, and consequently, low efficiency in poverty reduction. The primary sector, being a major contributor to low labor productivity in the country, offers promising opportunities for significant changes in economic efficiency, provided properly designed public policies target this sector.

Panels d and e in figure 7 indicate that efficiency in poverty reduction is negatively associated with both unemployment and informality. This relationship is well approximated by a linear function, especially in the case of unemployment, suggesting constant effects of labor market conditions on efficiency. The findings from these panels highlight that states with favorable labor market conditions, characterized by lower unemployment and informality rates, exhibit greater efficiency in poverty reduction. Additionally, the association with informality appears stronger than that with unemployment, consistent with the patterns observed in poverty rates in table 4. These results suggest that efforts aimed at poverty reduction could face challenges in the presence of a weak labor market and that public investment strategies targeting poverty alleviation may be less successful in the presence of high unemployment and especially of high informality.

FIGURE 7: Relationship between Efficiency and Determinants



(a) (b) (c)

(d) (e)

5 CONCLUSIONS

In this paper, we assess the efficiency of poverty reduction at the state level in Bolivia spanning the years 2000 to 2021. Our empirical approach extends existing research on pro-poor growth and the efficiency of public spending. By departing from the assumption of full efficiency in poverty alleviation, we estimate efficiency levels for each state and decompose these levels into permanent and transient components. Utilizing a GTRE instead of a DEA or FDH approach enables us to incorporate a diverse set of variables into the efficiency computation, allowing for an analysis of the association between inputs and poverty reduction.

Our key finding is that the majority of inefficiency in poverty reduction in Bolivia is of a permanent nature, indicating that inefficient poverty reduction is a persistent rather than a contingent phenomenon. This implies that short-term policies will have a limited impact and thatpoverty-alleviating strategies need to be redesigned so they focus on the long run. Our results suggest that Bolivian states, on average, could potentially reduce up to 82 percent of the poverty rate allowed by their macroeconomic conditions, but achieved an actual reduction of around 73 percent.

Regarding the relationship between economic sectors and efficiency, our findings indicate that states more intensively involved in the secondary and tertiary sectors and less engaged in the primary sector tend to exhibit higher efficiency. Furthermore, high levels of informality are associated with lower efficiency and increased public investment does not necessarily correlate with greater efficiency. Thus, rather than expanding public investment, optimizing the allocation of existing resources could be a more effective approach.

Efficiency in poverty reduction is found to be positively associated with the size of the tertiary sector. The relationship between efficiency and the primary and secondary sectors depends on their sizes, showing positive associations only if these sectors are substantial. States with lower levels of unemployment and informality appear to be more efficient, with informality playing a crucial role in efficiency. These results suggest that poverty-alleviating efforts may be hindered by a weak labor market, particularly when that market is characterized by high informality. Public investment aimed at reducing poverty may prove ineffective in the presence of high unemployment and, more critically, elevated informality.

Efforts toward poverty alleviation need to address the root causes of inefficiency and factors that impede those efforts' effectiveness. The persistent nature of inefficiency underscores the importance of a long-term policy focus over short-term interventions. Strengthening the labor market is identified as crucial for effective poverty alleviation policies.

Bolivia, once a success story in Latin America for its adept macroeconomic policy management and poverty reduction during the commodity boom, now faces a daunting economic landscape. The fading of the commodity boom, declining gas production, absence of policies for structural change, and the impact of COVID-19 have placed the country in its most challenging situation in nearly two decades. The government must now find ways to further reduce poverty amid less-favorable economic conditions. Efficiency in poverty reduction expenditures has thus become a crucial concern, given the current financial constraints and the need to direct resources to those truly in need. This requires a shift from universal aid programs to targeted measures, considering the high proportion of benefits reaching households who were not in poverty in the past.

The efficiency-informality relationship emerges as significant, suggesting that formalization policies that enhance tax collection, increase transfers, increase labor income, could contribute to productivity and growth. Redesigning poverty-alleviation policies to tackle informality could yield positive effects, though this necessitates a longer time frame. On the other hand, it would be necessary to improve the efficiency of public investment and their impact on poverty reduction, because we did not find a relationship between the size of such projects and poverty alleviation. For that reason, improving the design and quality of these programs through effective monitoring, evaluation mechanisms, community engagement, needs assessments, and strengthening of institutional capacities is of the utmost importance. Focusing the efforts on long-term poverty-alleviating policies and combining them with short-term measures like enhancing transfer efficiency could enable the Bolivian government to support ongoing poverty-reduction efforts more effectively.

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