IDB WORKING PAPER SERIES Nº IDB-WP-01216

Understanding the Growth of the Middle Class in Bolivia

Javier Beverinotti
Gustavo Canavire-Bacarreza
Alejandro Puerta

Inter-American Development Bank
Country Department Andean Group

July 2021

Understanding the Growth of the Middle Class in Bolivia

Javier Beverinotti
Gustavo Canavire-Bacarreza
Alejandro Puerta

July 2021

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Understanding the growth of the middle class in Bolivia / Javier Beverinotti, Gustavo Canavire-Bacarreza, Alejandro Puerta.
p. cm. — (IDB Working Paper Series ; 1216)

Includes bibliographic references.
1. Middle class-Bolivia-Econometric models. 2. Economic development-Social aspects-Bolivia-Econometric models. 3. Informal sector (Economics)-Bolivia-Econometric models. 4. Poverty-Bolivia-Econometric models. I. Canavire, Gustavo. II. Puerta, Alejandro. III. Inter-American Development Bank. Country Department Andean Group. IV. Title. V. Series.

IDB-WP-1216

http://www.iadb.org

Understanding the Growth of the Middle Class in Bolivia *

Javier Beverinotti†, Gustavo Canavire-Bacarreza‡, and Alejandro Puerta§

ABSTRACT

In this paper we aim to disentangle how sectoral economic growth affects the size of the middle class, using state-level data of Bolivia from 2000 to 2017 and breaking the three main economic activities into subsectors to attain more-specific results. Because the data from Bolivia are limited, we utilize a Bayesian hierarchical longitudinal model for small samples. We find that the commerce and services sectors have the biggest impact on the size of the middle class in Bolivia and that mining and agriculture have a similar though smaller effect. Our results also suggest that both formality and public social investment do have significant effects, albeit smaller ones.
Keywords: middle class, economic growth, informality
JEL CODES: C23, D63, I32, O41

*The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the Inter-American Development Bank, the World Bank, their Board of Directors, or the countries they represent.

†Inter-American Development Bank, Washington, DC, USA. Email: javierbe@iadb.org.
‡World Bank, Washington, DC, USA. Email: gcanavire@worldbank.org.
§Department of Economics, Universidad Carlos III, Madrid, Spain. Email: alpuerta@eco.uc3m.es.

1 Introduction

Improvements in the average quality of life are mirrored in poverty reduction and the enlargement of the middle class. While there is a wide literature that shows the potential of economic growth as a driver for poverty reduction and the growth of the middle class,[1] the channels through which this phenomenon occurs are less studied and mostly idiosyncratic. This is especially clear in developing countries, where the lack of data is a limiting factor in the examination of the sources of middle-class growth, which also limits the possibility of targeting policies.

Using data from the Ministry of Finance and National Statistical Office of Bolivia, in this paper we examine the economic sectors that strengthened the middle class in Bolivia, a highly informal country that has experienced a substantial decrease in poverty rates and an increase in the size of its middle class during the last two decades. In doing so, we leverage the framework developed by Ferreira et al. (2010) and Canavire-Bacarreza et al. (2018) and apply Bayesian techniques, which perform better in the presence of limited data.

Bolivia is an interesting context in which to examine the sources of growth of the middle class. The proportion of the country's population in the middle class more than doubled from 2000 to 2017 (from 13.4% to 28.3%), a period that saw the poverty rate fall from 64.5% to 39.3%. The rise in citizens' income levels is largely explained by the economic growth the country has experienced since 2006. However, it is not limited to being a dividend of the boom in the commodities market between 2006 and 2014. A rise in both labor and nonlabor income in different subsectors and the increase in the labor participation rate of individuals between the ages of 15 and 69 have also played a pivotal role in the decline of poverty. In order to continue to observe improvements in income levels and social indicators, especially in the presence of lower economic growth, it is essential to identify the channels that generated the biggest effects on these indicators, so as to know where state support could have the greatest impact. However, data limitations do not allow for a detailed examination of the channels through which positive impulses were generated in the middle class. With new sectoral data from the Ministry of Finance and the National Statistical Office, we examine the contribution that each economic subsector has made to the growth of the middle class, so as to enable a more precise identification of the possible channels fostering the growth of the middle class.

As noted by Ravallion and Bidani (1994), poverty-related estimates can be non-negligibly sensitive to both the definitions of poverty and of the poverty line used. Such definitions will naturally affect

[1] See Klasen (2008) for a review of the literature.

the corresponding definition of the middle class. To align this article's methodology with that of previous studies on this topic, it is necessary to construct a homogeneous definition of what the middle class represents. To categorize the Bolivian population by income level, we make use of the income variable of the Inter-American Development Bank's (IDB) sociometer. Accordingly, the vulnerable class is composed of households whose income is less than twice the poverty line and the middle class consists of households whose income is greater than twice but less than ten times the poverty line. It should be noted that the poor population is composed of those households with an income below the poverty line and the rich population by those with an income of more than ten times the poverty line. Similarly, when assessing the impact of growth on poverty reduction, the estimated magnitude and significance depends greatly on the definition of economic growth (Adams Jr, 2004). Since we aim to measure the impact of sectoral growth on the middle class, we use the sectoral GDP estimated by the Instituto Nacional de Estadística (INE), rather than changes in consumption. Our results suggest that services and commerce have had the biggest impact on the growth of the middle class in Bolivia, with mining and agriculture contributing to a lesser degree. These results are aligned with the wage compression argument, where the wages of low-skilled workers increased more than those in the skilled sector (Canavire-Bacarreza and Rios-Avila, 2017). We also find that though formality may play a statistically significant role in the growth of the middle class,[2] its effect is limited, in large part due to the significant size of the middle class in the country.

The remainder of this paper proceeds as follows: section 2 presents a brief description of the measurement of poverty and a literature review. In section 3, data and methodology are presented. Section 4 presents the main results. Section 5 concludes.

2 The Middle Class and Economic Growth

The literature on growth and poverty is extensive and has evolved significantly over time. However, there is limited literature devoted to the channels through which economic growth affects the middle class, with the bulk of the existing literature tackling the effects of economic growth on poverty. One of the first attempts to examine empirically the relationship between economic growth, poverty, and inequality was Ravallion and Huppi (1991). These authors found that increases in average real consumption (along with improvements in overall equity) contributed to poverty alleviation in the case of Indonesia. Two subsequent relevant attempts to assess poverty reduction in developing countries are Chen et al. (1994) and Ravallion (1995). Chen et al. (1994) found that poverty tends

[2] We identify as informal those workers who do not participate in social security systems.

to rise as the aggregate population of the developing world does, but that, given the diversity of the impacts on inequality, no systematic bivariate relationship can be identified between growth and inequality. Ravallion (1995), on the other hand, found a statistically significant negative relationship between growth in per capita consumption and the number of people living on less than a dollar per day. This result was reinforced by Ravallion and Chen (1999), who found a correlation between the decline in poverty and the growth in mean incomes. More recently, Dollar and Kraay (2002) found that as overall average income rises, so does the bottom quintile's average income.

Regarding sectoral growth and its impact on poverty reduction in developing countries, studies have looked at the agricultural sector alone, other specific nonagricultural sectors, and compared the former to the latter (Suryahadi et al., 2009). For example, Ravallion and Datt (1996b) found that growth in both the service and agricultural sectors reduce poverty more than growth in the manufacturing sector in India. Such findings led them to propose that fostering growth in the primary and tertiary sectors in rural areas is crucial for poverty reduction. Ravallion and Datt (1999) reinforced the importance of the agricultural sector in poverty alleviation in India, a view that is supported by evidence for China (Montalvo and Ravallion, 2009; Ravallion and Chen, 2009) and Indonesia (Thorbecke and Jung, 1996; Sumarto and Suryahadi, 2007; Suryahadi et al., 2009). On the other hand, there is evidence that the secondary sector has a bigger impact than the agricultural sector in the cases of Taiwan (Warr, 1998) and Peru (Canavire-Bacarreza et al., 2018). Finally, Ferreira et al. (2010) explored the direct relationship between growth and poverty reduction across all sectors in Brazil. They found that services sector growth had a substantially bigger effect in terms of poverty reduction than growth in the agriculture or industry sector.

Such variety in results indicates that reinforcement of sectors with the aim of reducing poverty needs to be country specific. However, the methods applied in this literature are usually not robust in the presence of limited data. Moreover, the question of whether the impact on poverty reduction is potentially subsector specific rather than sector specific has not been taken up. The isolation of subsectors enables the disentangling of economic growth's impact on middle-class size and in turn more insightful and effective policy planning.

3 Data and Methodology

3.1 Data

To analyze the potential relationship between economic growth by sector and the growth of Bolivia's middle class we use state-level data from 2000 to 2017.[3] Using economic indicators from INE and public sector investment from the Ministry of Finance, we build a data set for the nine Bolivian states (*departamentos*) and include controls for government investment (by sector), inflation rate (due to the regressive nature of the inflation tax), and terms of trade.

In Table 1, we observe Bolivia's wealth distribution by different income groups—the poor, vulnerable, middle class, and rich—from 2000 to 2017. In 2000, more than 3 out of 5 Bolivians were

TABLE 1: Bolivia's wealth distribution (%)

Year	Poor	Vulnerable	Middle class	Rich
2000	64.53	21.39	13.24	0.84
2001	70.47	17.78	10.94	0.81
2002	70.83	17.10	11.21	0.86
2003	61.62	22.37	15.03	0.98
2005	61.03	21.37	16.29	1.30
2006	58.42	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	42.72	31.03	25.63	0.62
2017	39.25	31.86	28.34	0.54

Source: INE Household Surveys.

considered poor and nearly 1 out of 10 belonged to the middle class. Eighteen years later, 2 out of 5 Bolivians were considered poor and almost 3 out of 10 considered middle class. During that time, Bolivia had an average annual economic growth rate of 4.4%. The correlation between this annual growth and the rates of growth of the poor and middle classes is -0.659 and 0.620, respectively.

[3]While the household surveys are representative at the state level since 2011, we expand the data backwards to obtain a larger data set at the risk of losing representativeness. We test by grouping states by the three regions of the initial surveys and the results are consistent

Conditional on the growth of the vulnerable class (10 percentage points), middle-class growth did not result in a decrease in the size of the rich class, because of the middle class's insignificant share of total wealth (this class is always less than 1.3% of the total population). This suggests an improvement in citizens' quality of life—in particular, a substantial migration of the poor into the vulnerable and middle classes.

3.2 Methodology

We estimate a Bayesian longitudinal model to solve endogeneity problems associated with the "fixed effects." This approach also allows us to work around the issue of the small sample size, which negatively affects the likelihood of a variable being statistically significant (Button et al., 2013). Because a Bayesian approach does not rely on large sample sizes (Gelman et al., 2013) and Bayesian estimates tend to behave better when dealing with small sample sizes (Hox et al., 2012), we rely on this approach for estimation.

Another main difference of our approach concerns specification. Our isolation of subsectors has a substantial effect on parameter estimates, which suggests an inaccurate inference in its absence. Additionally, we find that informality plays a determinant role in middle class size in Bolivia, a country with historical high rates of informality.

3.2.1 Bayesian empirical strategy

Our econometric approach will be Bayesian, mainly to control for "fixed effects" without relying on their independence from the covariates or a transformation of the variables. As noted above, we also adopt this approach to tackle the small size of the data sample, and because Bayesian modelling enables statistical inference based on the conditional posterior distributions, rather than point estimates, so public policy proposals are more accurate. At the same time, to assess robustness of parameter estimates we also perform frequentist estimation.

Due to the data structure and the necessity of solving for the endogeneity associated with the unobserved heterogeneity, a tailor-made model is the Bayesian hierarchical Gaussian linear regression model, which has the following representation:

$$y_i = X_i\beta + b_i + \epsilon_i$$

where y_i is the (log of) the percentage of the middle class within the population[4], X_i is a set of covariates comprising subsectoral growth and public spending, β are the location parameters associated to the fixed effects, b_i are the random effects,[5] and ϵ_i is the idiosyncratic disturbance. Since we are in a Bayesian framework, we need to set priors for the location and scale parameters. We set $\alpha_0 = \delta_0 = 0.001$ (Spiegelhalter et al., 2003), $v_0 = 1$ and $d_0 = 10$ (Martin et al., 2011), center at 0 the fixed effect parameters, and use an overdispersed diagonal covariance matrix with elements equal to 1.0E6. In other words, we use "non-informative priors."

The setting for the Gibbs Sampler is the following:

$$\pi(\beta, b_i, \sigma^2, \sigma_b^2 | y_{it}) \propto f(y_{it}|\beta, b_i, \sigma^2, \sigma_b^2)\pi(\beta)\pi(\sigma^2)\pi(\sigma_b^2).$$

Taking into account that $\boldsymbol{y}_i|\boldsymbol{\beta}, \sigma_b^2, \sigma^2 \sim \mathcal{N}(\boldsymbol{X}_i\boldsymbol{\beta}, \boldsymbol{V}_i)$ where $\boldsymbol{V_i} = \sigma^2 \boldsymbol{I}_{n_i} + \sigma_b^2 \boldsymbol{i}_{n_i}\boldsymbol{i}'_{n_i}$ and $\boldsymbol{i}_{n_i}$ is a vector of ones, then

$$y_{ij}|\boldsymbol{\beta}, \sigma^2, \boldsymbol{b}, \boldsymbol{y}, \boldsymbol{X}, \boldsymbol{W} \propto \mathcal{N}(\boldsymbol{x}'_{ij}\boldsymbol{\beta} + b_i, \sigma^2),$$

$$\boldsymbol{\beta}|\sigma^2, \sigma_b^2, \boldsymbol{y}, \boldsymbol{X} \sim \mathcal{N}(\boldsymbol{\beta}^*, \boldsymbol{B}),$$

$$b_i|\boldsymbol{\beta}, \sigma^2, \sigma_b^2, \boldsymbol{y}, \boldsymbol{X} \sim \mathcal{N}(b_i^*, s_i^*),$$

$$\sigma_b^2|\boldsymbol{b} \sim \mathcal{IG}(d^*, v^*),$$

$$\sigma^2|\boldsymbol{\beta}, \sigma_b^2, \boldsymbol{b}, \boldsymbol{y}, \boldsymbol{X} \sim \mathcal{IG}(\alpha^*, \delta^*),$$

where $\boldsymbol{B} = (\boldsymbol{B}_0^{-1} + \sigma^{-2}\sum_{i=1}^n \boldsymbol{X}_i'\boldsymbol{V}_i^{-1}\boldsymbol{X}_i)^{-1}$, $\boldsymbol{\beta}^* = \boldsymbol{B}(\boldsymbol{B}_0^{-1}\boldsymbol{\beta}_0 + \sigma^{-2}\sum_{i=1}^n \boldsymbol{X}_i'\boldsymbol{V}_i^{-1}\boldsymbol{y}_i)$, $s_i^* = (\sigma_b^{-2} + n_i\sigma^{-2})^{-1}$, $b_i^* = s_i^*(\sigma^{-2}\boldsymbol{i}'_{n_i}(\boldsymbol{y}_i - \boldsymbol{X}_i\boldsymbol{\beta}))$, $d^* = \frac{d_0+m}{2}$ and $v^* = 2d_0v_0 + 2\sum_{i=1}^m b_i^2$, $\alpha^* = \alpha_0 + \frac{1}{2}\sum_{i=1}^m n_i$ and $\delta^* = 1/\delta_0 + \frac{1}{2}\sum_{i=1}^m(\boldsymbol{y}_i - \boldsymbol{X}_i\boldsymbol{\beta} - \boldsymbol{i}_{n_i}b_i)'(\boldsymbol{y}_i - \boldsymbol{X}_i\boldsymbol{\beta} - \boldsymbol{i}_{n_i}b_i)$.

An advantage of this hierarchical longitudinal model is that it does not require the panel to be either balanced or equidistant; it just requires that several observations exist at different points in time.

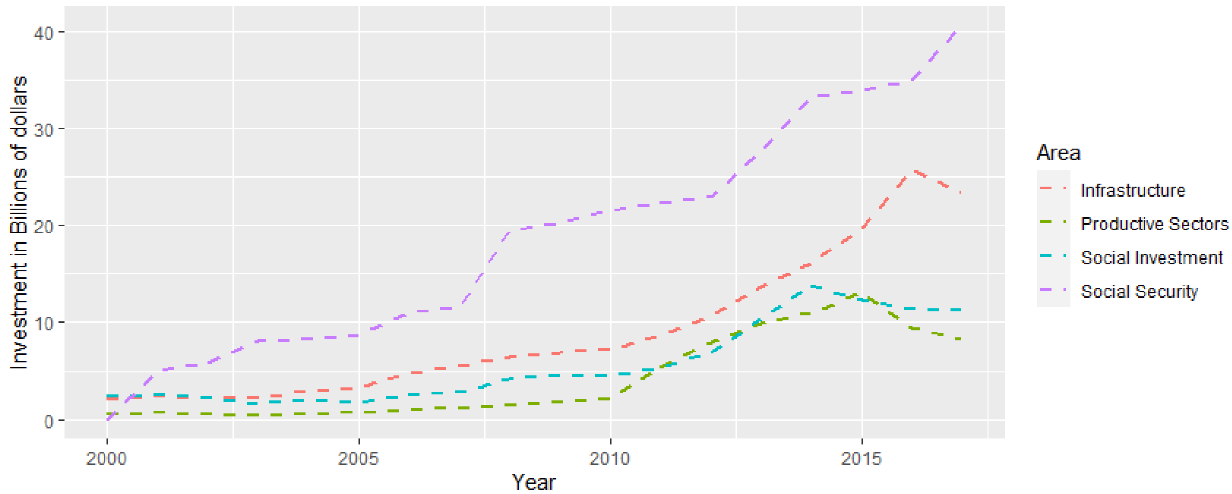
3.2.2 Specification

As opposed to Ferreira et al. (2010) and Canavire-Bacarreza et al. (2018), our particular interest is in middle-class size. These scholars extend the proposition from Ravallion and Datt (1996a) in order to model the growth of the poverty rate. The goal of modeling this in differences is twofold, as the authors seek to represent the dependent variable growth rate instead of the poverty reduction

[4]This leads to an interpretation of elasticity of sectoral growth.

[5]These correspond to the so-called fixed effects in the frequentist econometric literature.

FIGURE 1: Public Investment by Area 2000–2017



rate in logs and to eliminate the fixed effect in the error term (Ferreira et al. (2010)). However, differencing leads to a decrease in sample size, an outcome that, given our reduced sample, we attempt to avoid. Additionally, we are interested in middle-class size rather than the poverty rate. Therefore, instead of applying the differentiation operator, we adopt a Bayesian approach to deal with the fixed effect. However, we incorporate the weighting by share from Ravallion and Datt (1996a), Ferreira et al. (2010), and Canavire-Bacarreza et al. (2018). Consistent with this, we model the (log) middle-class size ($lnMC_{it}$) in state i at year t, which depends on the economic (log) size of the sector J lnY_{it}^J weighted by its share $s_{i,t-1}^J = \frac{Y_{i,t-1}^J}{Y_{i,t-1}}$.

TABLE 2: Public Investment by area 2000–2017 (USD, thousands)

Year	Productive sectors	Infrastructure	Social investment	Social security
2000	0.55	2.02	2.39	0.00
2001	0.61	2.29	2.53	5.01
2002	0.59	2.22	2.19	5.76
2003	0.43	2.28	1.64	8.08
2004	0.52	2.96	1.99	8.26
2005	0.67	3.26	1.73	8.68
2006	0.92	4.81	2.45	10.95
2007	1.17	5.50	2.74	11.53
2008	1.43	6.42	4.19	19.52
2009	1.79	6.93	4.47	20.40
2010	2.20	7.20	4.41	21.50
2011	5.39	8.66	5.31	22.32
2012	7.91	10.73	6.86	22.96
2013	9.95	13.67	10.32	27.81
2014	10.93	16.18	13.80	33.18
2015	13.15	19.78	12.39	33.93
2016	9.45	25.83	11.39	35.10
2017	8.23	23.46	11.29	40.60

Source: Ministry of Finance Bolivia

To identify the marginal effect of economic growth on middle-class size consistently, we control for macroeconomic variables and public investment. Our macroeconomic covariates include (1) inflation, to control for potential effects of monetary policy on the distribution of income and the inflation tax; (2) terms of trade, to account for the commodity boom and the fall in the price of commodities between 2013 and 2017; and (3) informality rate. In 2000, the average informality rate was 86.85% and in 2017 it was 82.41%; for that year, Bolivia was 17^{th} in the ranking of countries with the highest informality rates (International Labour Organization, 2017). As mentioned above, we control for public investment in productive sectors, infrastructure, social investment, and social security. In Table 2, we show descriptive statistics for each area and Figure 1 depicts the growth of each one. As can be seen, most of the investment comes from social security, follow by investment in infrastructure.

The aforementioned specification leads to the following equation:

$$\begin{aligned} lnMC_{it} = \beta_0 + \alpha_i + \beta_1 s^{P}_{i,t-1} lnY^{P}_{it} + \beta_2 s^{S}_{i,t-1} lnY^{S}_{it} + \beta_3 s^{T}_{i,t-1} lnY^{T}_{it} \\ + \sum_{k=1}^{4} \phi_k lnX^{k}_{i,t-1} + \phi_5 GCPI_t + \phi_6 lnTOT_t + \phi_7 INF_{it} + \epsilon_{it} \end{aligned} \tag{1}$$

where β_i with $i = 0, 1, ..., 3$, ϕ_k, $k = 1, ..., 6$ and α_i, with $i = 1, ..., 9$ are the parameters to estimate; $lnMC_{it}$ is the (log) of the size of the middle class, Y^{J}_{it}, with $J = P, S, T$ representing the product of the $J - th$ sector (P stands for primary, S for secondary, and T for tertiary); X^{k}_{it} is government investment in the $k - th$ area; TOT_t are the terms of trade at time t; $GCPI_t$ is the inflation at time t; INF_{it} is the informality rate; and ϵ_{it} is the idiosyncratic disturbance. Nonetheless, as is shown in section 4, to disentangle marginal effects, it is convenient to isolate subsectors. Consequently, we propose the following estimable equation:

$$\begin{aligned} lnMC_{it} = \beta_0 + \alpha_i + \beta_1 s^{'ag}_{i,t-1} lnY^{'ag}_{it} + \beta_2 s^{'min}_{i,t-1} lnY^{'min}_{it} + \beta_3 s^{'com}_{i,t-1} lnY^{'com}_{it} \\ + \beta_4 s^{'cons}_{i,t-1} lnY^{'cons}_{it} + \beta_5 s^{'man}_{i,t-1} lnY^{'man}_{it} + \beta_6 s^{'serv}_{i,t-1} lnY^{'serv}_{it} \\ + \sum_{k=1}^{4} \phi_k lnX^{k}_{i,t-1} + \phi_5 GCPI_t + \phi_6 lnTOT_t + \phi_7 INF_{it} + \epsilon_{it} \end{aligned} \tag{2}$$

where ag stands for agriculture, min for mining, com for commerce, $cons$ for construction, man for manufacturing, and $serv$ for services.

4 Results

Table 3 reports the results of estimating equation (2). The first column presents results from a fixed effects model and the second from the Bayesian model. For the Gibbs sampler, we obtain posterior chains of dimension 2,500 (total iterations 10,000, burn-in 10,000, and thin parameter 4). The coefficients reported for the Bayesian models in Table 3 correspond to the mean of the posterior distribution for each parameter, and the credible intervals are estimated with the highest posterior density intervals. (HPDI)[6]. The significance of Bayesian estimates depends on the HPDI not passing through zero.

The magnitudes of the marginal effects of both models are very similar. The most relevant difference is that according to the frequentist model, the secondary sector does not have a significant effect on middle-class size. However, one would also infer that there is not an inflationary tax and that the only relevant public investment is that affecting the productive sectors. Finally, the frequentist model asserts that the terms of trade do not have a significant effect on middle-class size. None of these conclusions can be drawn from the Bayesian model. In fact, all of the covariates are significant at the 99% confidence level. Based on the results presented in Table 3, policy makers could think about supporting the tertiary sector, since it is the sector with the biggest magnitude. Even though the primary sector has a smaller magnitude, it has a substantial effect on middle class size and could also be supported. According to the Bayesian model, the secondary sector does have a significant effect, but it is substantially smaller than the other two.

We exploit the richness of our dataset by breaking sectors into subsectors in order to disentangle specific effects. We turn now to the specification with the isolation of subsectors. The results of estimating equation (2) are reported in Table 4.

The first thing to remark upon from Table 4[7] is that all the Bayesian estimates values are very similar to the frequentist ones. However, there is one remarkable difference: most of the regressors are not significant in the frequentist model. In fact, based on a statistical inference from the frequentist model, it is the case that only commerce and services have a significant effect on middle-class size. Column 2 of Table 4 indicates that if one specific subsector of the primary sector should be supported with the aim of increasing middle-class size, it should be mining rather than agriculture.

[6]This corresponds to 95% of the mass of the posterior, excluding both tails, which is "comparable" with the frequentist confidence intervals at a 95% confidence level.

[7]We perform two robustness checks to motivate our specification. First, we estimate the same model as in Canavire-Bacarreza et al. (2018) (see Table A1). Second, we perform a simple simulation to show evidence that nine observational units (states) are enough for accurate identification for the location parameters (see Table A2).

TABLE 3: Regressions results by sectors

	(Fixed Effects) $lnMC_{it}$	(Bayesian Longitudinal) $lnMC_{it}$
lnY_{it}^P	0.813***	0.766***
	[0.222,1.405]	[0.6524,0.8833]
lnY_{it}^S	0.343	0.2966***
	[-0.421,1.108]	[0.1438,0.4456]
lnY_{it}^T	1.082***	1.0256***
	[0.431,1.734]	[0.8967,1.1544]
$GCPI$	-0.413	-0.3873**
	[-2.202,1.376]	[-0.7499,-0.0707]
Productive Sectors	0.110**	0.114***
	[0.0262,0.193]	[0.099,0.1309]
Infrastructure	-0.0481	-0.0464***
	[-0.151,0.0548]	[-0.066,-0.0281]
Social Investment	0.0749	0.0784***
	[-0.100,0.250]	[0.0456,0.1096]
Social Securities	0.0653	0.0684**
	[-0.239,0.370]	[0.0082,0.1241]
$lnTOT$	0.158	0.1563***
	[-0.103,0.420]	[0.1057,0.2029]
INF	-0.0258***	-0.0262***
	[-0.0382,-0.0135]	[-0.0285,-0.0238]
Constant	-9.459***	-8.8683***
	[-16.19,-2.726]	[-10.3284,-7.4958]
N	117	117

Note: 95% confidence intervals in brackets for the frequentist model.
Highest density posterior intervals with a 95% credible mass in brackets for the Bayesian model.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In fact, the size of the effect of the former is almost two times that of the latter. We also infer that the secondary sector does not have a significant effect on middle-class size, since it is comprised of the construction and manufacturing sectors, neither of which have a statistically significant effect. According to Table 4, the most effective subsectors in terms of increasing middle-class size are commerce and services, in that order. Notice that the conclusions here are similar to those of Table 3, but are more precise. Additionally, the magnitudes of the estimates associated with the commerce and services subsectors suggest that their impacts would have been underestimated had they been grouped in the tertiary sector (see Table 3).

On average, public investment has a positive effect on middle class size. Except for infrastructure, which has a small negative effect, all the other covariates regarding public investment are significant and positive. The one with the biggest effect is social security, which comprises the cash transfer programs of Renta Dignidad, Bono Juana Azurduy, and Bono Juancito Pinto. Based on a statistical inference, we find that only investment in the productive sectors has a positive and significant effect on middle- class size, which is misleading, according to the Bayesian estimates.

Regarding the macroeconomic controls, all of them have the expected direction. However, we find

TABLE 4: Regressions results by subsectors

	(Fixed Effects) $lnMC_{it}$	(Bayesian Longitudinal) $lnMC_{it}$
lnY_{it}^{ag}	0.277	0.2823***
	[-0.624,1.178]	[0.1215,0.4296]
lnY_{it}^{min}	0.553	0.5218***
	[-0.132,1.239]	[0.4021,0.6437]
lnY_{it}^{com}	1.169**	1.141***
	[0.234,2.104]	[0.9745,1.3061]
lnY_{it}^{cons}	0.106	0.0813
	[-0.819,1.031]	[-0.0775,0.2464]
lnY_{it}^{man}	-0.0489	-0.0357
	[-0.991,0.893]	[-0.201,0.1231]
lnY_{it}^{serv}	0.920**	0.8575***
	[0.113,1.728]	[0.7109,1.0076]
$GCPI$	-0.104	-0.0683
	[-1.908,1.700]	[-0.3766,0.2685]
Productive Sectors	0.107**	0.1112***
	[0.0208,0.193]	[0.096,0.1271]
Infrastructure	-0.0459	-0.0467***
	[-0.158,0.0658]	[-0.0664,-0.0285]
Social Investment	0.0687	0.0731***
	[-0.109,0.247]	[0.0408,0.1029]
Social Security	0.162	0.1568***
	[-0.156,0.480]	[0.1051,0.2159]
$lnTOT$	0.149	0.1335***
	[-0.148,0.446]	[0.0752,0.1842]
INF	-0.0255***	-0.026***
	[-0.0380,-0.0130]	[-0.0284,-0.0236]
Constant	-6.474	-6.0231***
	[-14.29,1.345]	[-7.5118,-4.5239]
N	117	117

95% confidence intervals in brackets for the frequentist model.
highest density posterior intervals with a 95% credible mass in brackets for the Bayesian model.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

that when we control for all the economic sub-sectors, the inflation tax does not have a significant effect on middle class size. As expected, better terms of trade have a positive effect. Finally, we find that informality rate has a negative and significant effect on middle class size. As previously mentioned, Bolivia has an informality rate over 80%, which is among the highest in the region. Table 4 suggests that a decrease in informality has a positive effect on middle class size.

5 CONCLUSIONS

In this paper, we find that dividing economic sectors into subsectors is crucial for identifying the causal effects of sector growth on the growth of the middle class. Our results suggest that when a frequentist approach is performed, in the presence of a small sample size nonsignificance could be misled by power instead of the absence of causality. A Bayesian approach allows us to obtain chains consistent with a frequentist approach's point estimates and make inferences on the basis of the whole posterior distribution.

Our results suggest that policy makers should consider supporting both the commerce and services subsectors in order to increase middle-class size. Supporting the agriculture and mining subsectors would have a positive impact as well, though to a lesser extent. Overall, public investment has helped with poverty reduction. We also find that better terms of trade and lower levels of informality tend to increase middle-class size.

The Bolivian economy will be greatly affected by the onset of the COVID-19 pandemic, as will the rest of Latin America. Given this scenario, it is expected that the middle class will be severely affected. Knowing which subsectors can best support the recovery of the middle class is important not only for resource allotment, but also for maximizing the efficiency of public spending, which will be seriously restricted in this situation.

References

Adams Jr, R. H. (2004). Economic growth, inequality and poverty: estimating the growth elasticity of poverty. *World Development 32*(12), 1989–2014.

Button, K. S., J. P. Ioannidis, C. Mokrysz, B. A. Nosek, J. Flint, E. S. Robinson, and M. R. Munafò (2013). Power failure: why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience 14*(5), 365–376.

Canavire-Bacarreza, G., M. Jetter, and M. Robles (2018). When does economic growth reduce poverty and strengthen the middle class? a state-level, sector-specific analysis of peru. *Southern Economic Journal 84*(4), 1067–1087.

Canavire-Bacarreza, G. and F. Rios-Avila (2017). On the determinants of changes in wage inequality in urban bolivia. *Journal of Human Development and Capabilities 18*(4), 464–496.

Chen, S., G. Datt, and M. Ravallion (1994). Is poverty increasing in the developing world? *Review of Income and Wealth 40*(4), 359–376.

Dollar, D. and A. Kraay (2002). Growth is good for the poor. *Journal of economic growth 7*(3), 195–225.

Ferreira, F. H., P. G. Leite, and M. Ravallion (2010). Poverty reduction without economic growth?: Explaining brazil's poverty dynamics, 1985–2004. *Journal of Development economics 93*(1), 20–36.

Gelman, A., J. B. Carlin, H. S. Stern, D. B. Dunson, A. Vehtari, and D. B. Rubin (2013). *Bayesian data analysis*. CRC press.

Hox, J. J., R. van de Schoot, and S. Matthijsse (2012). How few countries will do? comparative survey analysis from a bayesian perspective. In *Survey Research Methods*, Volume 6, pp. 87–93.

International Labour Organization (2017). *ILOSTAT database*. Accessed December 9, 2019.

Klasen, S. (2008). Economic growth and poverty reduction: Measurement issues using income and non-income indicators. *World Development 36*(3), 420–445.

Martin, A. D., K. M. Quinn, and J. H. Park (2011). MCMCpack: Markov chain monte carlo in R. *Journal of Statistical Software 42*(9), 22.

Montalvo, J. G. and M. Ravallion (2009). *The pattern of growth and poverty reduction in China*. The World Bank.

Ravallion, M. (1995). Growth and poverty: Evidence for developing countries in the 1980s. *Economics letters 48*(3-4), 411–417.

Ravallion, M. and B. Bidani (1994). How robust is a poverty profile? *The world bank economic review 8*(1), 75–102.

Ravallion, M. and S. Chen (1999). *What can new survey data tell us about recent changes in distribution and poverty?* The World Bank.

Ravallion, M. and S. Chen (2009). China's (uneven) progress against poverty. In *Governing Rapid Growth in China*, pp. 65–111. Routledge.

Ravallion, M. and G. Datt (1996a). How important to india's poor is the sectoral composition of economic growth? *The World Bank Economic Review 10*(1), 1–25.

Ravallion, M. and G. Datt (1996b). India's checkered history in fight against poverty: are there lessons for the future? *Economic and Political Weekly*, 2479–2485.

Ravallion, M. and G. Datt (1999). *Why have some Indian states done better than others at reducing rural poverty?* The World Bank.

Ravallion, M. and M. Huppi (1991). Measuring changes in poverty: a methodological case study of indonesia during an adjustment period. *The World Bank Economic Review 5*(1), 57–82.

Spiegelhalter, D., T. Best, W. Gilks, and D. Lunn (2003). BUGS: Bayesian inference using Gibbs sampling. Technical report, MRC Biostatistics Unit, England. www.mrc-bsu.cam.ac.uk/bugs/.

Sumarto, S. and A. Suryahadi (2007). Indonesia country case study. *Beyond Food Production: The Role of Agriculture in Poverty Reduction. Food and Agriculture Organization of the United Nations and Edward Elgar, Cheltenham*.

Suryahadi, A., D. Suryadarma, and S. Sumarto (2009). The effects of location and sectoral components of economic growth on poverty: Evidence from indonesia. *Journal of Development Economics 89*(1), 109–117.

Thorbecke, E. and H.-S. Jung (1996). A multiplier decomposition method to analyze poverty alleviation. *Journal of Development Economics 48*(2), 279–300.

Warr, P. G. (1998). *Poverty, inequality and economic growth in Taiwan*. Department of Economics, Research School of Pacific and Asian Studies ....

A Robustness Check

A.1 State specific coefficients

Not surprisingly, almost none of the parameters are different from zero when estimating state-specific parameters (since there are very few degrees of freedom). However, the coefficients that are constant across states are very similar to those in Table 4. These results form the basis for our contention that it is better to estimate parameters that are constant across states.

Table A1: State-specific effects

	(Frequentist) $lnMC_{it}$	(Bayesian) $lnMC_{it}$
$GCPI$	-1.754	-1.0294***
	[-4.308,0.800]	[-1.3111,-0.7067]
Productive Sectors	0.131**	0.1177***
	[0.0245,0.238]	[0.1026,0.1328]
Infrastructure	-0.0539	-0.0506***
	[-0.206,0.0978]	[-0.0711,-0.031]
Social Investment	0.102	0.0658***
	[-0.131,0.335]	[0.0343,0.0967]
Social Securities	-0.0301	0.1625***
	[-0.579,0.519]	[0.1025,0.2319]
$lnTOT$	0.00452	0.3004***
	[-0.00185,0.0109]	[0.2375,0.3653]
INF	-0.0340***	-0.0340***
	[-0.0511,-0.0168]	[-0.0511,-0.0168]
$lnY_{it}^{ag,Coch}$	-11.29*	-1.9076
	[-24.70,2.116]	[-8.6414,4.576]
$lnY_{it}^{ag,Pot}$	-6.393*	-4.6408**
	[-13.25,0.462]	[-9.6758,-0.2383]
$lnY_{it}^{min,Coch}$	-12.35*	-0.4722
	[-25.12,0.421]	[-3.8402,2.5981]
$lnY_{it}^{com,Coch}$	-15.33*	-0.8363
	[-31.19,0.526]	[-5.8771,4.7378]
$lnY_{it}^{ser,Coch}$	-7.999*	0.3929
	[-17.21,1.209]	[-1.915,2.9165]
$lnY_{it}^{man,Coch}$	-6.955*	-0.3493
	[-14.01,0.100]	[-2.0043,1.2442]
$lnY_{it}^{cons,Coch}$	-6.436*	-1.8926
	[-14.10,1.226]	[-6.8729,2.41]
$lnY_{it}^{cons,Pot}$	-2.098**	-1.915***
	[-4.122,-0.0742]	[-3.1941,-0.513]
N	117	117

95% confidence intervals in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.2 SIMULATIONS

We perform a simple simulation exercise to demonstrate that proper estimates for the location parameters can be attained with nine observational units. To do so we perform the following simulation:

$$y_{it} = \beta_0 + \mathbf{X}'_{it}\beta + b_i + u_i$$

Where i has 9 different units and t 13. $\mathbf{X}_{it} \sim \mathcal{N}(0_{13}, \mathbf{I}_{13})$ (which is the number of covariates in our model excluding the constant); $\beta = (\beta_1, \beta_2, ..., \beta_{13})$ is a vector of length 13 with alternating values of 0.3 and -0.3; $\beta_0 = -0.3$ and $(b_i, u_i)' \sim \mathcal{N}(0_2, \mathbf{I}_2)$. As depicted in Table A2, the point estimates (mean) for the location parameters are very close to the real ones and all of the real values lie on the 95% HDI.

TABLE A2: Summary for location parameters

	y_{it}
β_0	-0.3926
	[-3.0965,2.4115]
β_1	0.3392***
	[0.1027,0.5517]
β_2	-0.4786***
	[-0.6996,-0.2516]
β_3	0.1789*
	[-0.0273,0.3802]
β_4	-0.273**
	[-0.5005,-0.0605]
β_5	0.3046***
	[0.1092,0.5166]
β_6	-0.3563***
	[-0.5882,-0.128]
β_7	0.345***
	[0.1172,0.5636]
β_8	-0.2473**
	[-0.4684,-0.0296]
β_9	0.309***
	[0.0916,0.5167]
β_{10}	-0.1838*
	[-0.3832,0.0036]
β_{11}	0.2094*
	[-0.0229,0.4169]
β_{12}	-0.2382**
	[-0.4468,-0.043]
β_{13}	0.3526***
	[0.1701,0.5413]