Interaction Poverty, Growth and Inequality in Senegal

Dr. Mbaye AW

Higher Institute of Management Dakar, Senegal (ISM)
Email: *awmbaye[at]yahoo.fr*
https://orcid.org/0009-0004-5407-3034

Abstract: ***This article examines the links between poverty, income inequality, and economic growth in Senegal over the period 2000-2025 using a panel VAR model estimated by the GMM method. It analyzes the extent to which growth reduces poverty and whether this growth can be described as pro-poor. The results reveal significant bidirectional interactions between the three variables. An increase in GDP reduces poverty with a lag of one to two years, but an increase in inequality raises poverty and hinders future growth. Thus, only a combination of growth and inequality-reduction policies enables inclusive development.***

Keyword: Poverty; Income inequality; Senegal; Economic development; Living standard; Social inequality; Welfare analysis.

1. Introduction

Economic growth, as well as the elimination of inequality and extreme poverty, has been a major concern in recent years. For this reason, all development strategies have been oriented toward poverty reduction (Boccanfuso and Kaboré, 2003). In this context, the Sénégal 2050 Vision was developed. It is based on three pillars: a structural transformation of the economy through the consolidation of current growth drivers and the development of new sectors that create wealth, employment, and social inclusion; a significant improvement in the living conditions of the population, with stronger efforts to combat social inequalities while preserving the resource base and promoting the emergence of viable territories; and the strengthening of security, stability, and governance, the protection of rights and freedoms, and the consolidation of the rule of law.

From a theoretical perspective, the debate has focused on the nature of the relationship between growth and inequality (Kuznets, 1995; Stiglitz, 1969), but research has shown that this relationship is not systematic (Goudie and Ladd, 1999). In recent years, the debate on growth, inequality, and poverty has led to new concepts, including pro-poor and pro-rich growth (Baulch and Cullock, 1999; White and Anderson, 2000; Ravallion and Chen, 2002). Growth is considered pro-poor if changes in income distribution are favorable to the poor (Baulch and Cullock, 1999). The definition of pro-poor growth is therefore closely linked to poverty and inequality.

Empirically, Datt and Ravallion (1992) conducted a decomposition of poverty into growth effects and inequality effects. Similarly, Lachaud (1996) studied this relationship in three Sub-Saharan African countries, namely Burkina Faso, Ghana, and Mauritania. Along the same lines, Ali and Thorbecke (1998) showed that urban poverty is more sensitive to growth, while rural poverty is more responsive to changes in income distribution. In Senegal and Cameroon, the most favorable scenario for poverty reduction involves a combination of growth and inequality reduction (Boccanfuso and Kaboré, 2004; Fambon, 2005; Avom and Carmignani, 2008).

In this regard, an evaluation of poverty reduction requires an analysis of the degree of interaction or independence between growth, inequality, and poverty (Bourguignon, 2004). The objective of this paper is to establish the link between poverty, inequality, and growth in Senegal. Specifically, the study aims, on the one hand, to decompose poverty into growth effects and inequality effects, and, on the other hand, to analyze whether growth in Senegal is pro-poor or pro-rich. Senegal was chosen as the focus of investigation due to the high incidence of poverty in the country (46.7%, according to the Senegal Poverty Monitoring Survey, 2011), reflecting the limitations and exhaustion of poverty reduction policies implemented over several decades.

From a methodological standpoint, this study builds on the work of Datt and Ravallion (1993), Shorrocks and Shapley (1953), and Kakwani and Pernia (2001). By analyzing the sources of poverty variation, the goal is to determine the share attributable to changes in income distribution versus changes in average income. The traditional Gini index is not fully appropriate, as it does not allow one to conclude that a reduction in inequality necessarily reduces poverty. When inequality and poverty vary in the same direction, the observed change in the Gini index can provide only a weak indication of the quantitative effects on poverty. Therefore, it is possible to decompose any change in poverty in order to quantify the relative importance of improvements in living standards and redistribution. The decomposition of poverty variation can be expressed as the sum of the contributions of growth, redistribution, and a residual. The main drawback of this method is the presence of a residual, which can be quite substantial. This paper is organized into three sections. The first section presents a literature review on the links between poverty, growth, and inequality. The second section is devoted to the methodology. The final section presents the results and discusses their implications for economic policy

2. Literature Review

In this section, we analyze the theoretical and empirical relationships between poverty, inequality, and economic growth.

2.1 Theoretical Links between Poverty, Inequality, and Economic Growth

The debate on the relationship between growth and inequality dates back to Kuznets (1955) and was further developed within the neoclassical growth model by Stiglitz (1969). The findings of these pioneering studies highlight the existence of a reciprocal influence between these three variables.

The relationship, known as the Kuznets hypothesis (1955), suggests that the link between per capita income and inequality follows an inverted U-shaped curve. This hypothesis addresses the issue of wealth distribution during periods of economic growth. The curve can be divided into three phases according to the effects of evolving productive structures and the spread of wealth throughout the economy. First, in the early stages of development, the economy is characterized by very low income levels, with investment being the main driver of growth. In this context, inequalities can encourage growth by concentrating resources among those who save and invest the most. Second, as the economy reaches a more advanced stage of development, as in industrializing countries, inequalities initially increase due to the transition from a rural to an industrial economy. However, the slowdown in physical investment in favor of the development of sectors intensive in technology and human capital reduces the inequality constraint. Finally, when economic wealth becomes significant, inequalities stabilize while growth continues. In this phase, the decline in inequality is explained by the replacement of physical capital by human capital as the main driver of growth. Kuznets' analysis is particularly interesting because it adopts a dualistic structure, which can be applied to both Western and developing countries.

Moreover, the neoclassical growth and distribution model of Stiglitz (1969) explains a similar evolution based on individual accumulation behavior.

The previous discussion focuses on only one aspect of the growth-distribution relationship. A second aspect posits that inequalities are not merely an outcome but also play a central role in determining growth (Gala and Zeira, 1993; Pearson and Tabellini, 1994; Barro, 1999). According to these authors, initial inequalities are associated with lower growth rates. They rely on credit market imperfections, democracy, and economies of scale to show how progressive redistribution can strengthen growth.

The credit market imperfection hypothesis argues that redistributing capital from firms to individuals or populations without access to credit improves efficiency, investment, and economic growth. The democracy-related argument suggests that high inequality in a redistributive democracy leads to increased redistribution and reduced capital accumulation. When voting rights extend to the majority of citizens, the rate of redistribution is determined by the median voter, directly or indirectly influencing the economy's growth rate (Bourguignon, 2004). Finally, the economies-of-scale argument posits that severe consumption inequality reduces demand for goods and, consequently, limits the ability to benefit from economies of scale in the production of certain consumer goods (Shleifer and Vishny, 1998). Similarly, Bourguignon (2004) shows that the relationship between growth and inequality is reciprocal, which justifies the debate on compensating growth effects with inequality effects.

From this discussion, it appears that growth may be either unequal or neutral in its impact on distribution. No consensus has emerged regarding the neutrality of growth, implying that growth policies are crucial in all development strategies. Given the limitations of traditional poverty reduction policies, the focus has recently shifted to pro-poor growth.

The concept of pro-poor growth emphasizes both changes in inequality and the incidence of poverty. Growth is considered pro-poor if changes in income distribution benefit the poor (Baulch and Cullock, 2000; Kakwani and Pernia, 2001). This definition focuses on inequality changes, whereas Ravallion and Chen (2003) define pro-poor growth as growth that improves household well-being, which would be accompanied by a reduction in poverty indices.

Boccanfuso and Ménard (2009) distinguish between relative and absolute definitions of pro-poor growth. Growth is considered pro-poor if the income growth rate of poor individuals exceeds that of non-poor individuals (White and Anderson, 2000; Klasen, 2003; Baulch and Cullock, 1999; Kakwani and Pernia, 2001; Kakwani and Son, 2002). This definition faces three criticisms:

1) By focusing on inequalities, the relative definition may yield suboptimal results for both poor and non-poor individuals;
2) An economic recession could be deemed pro-poor if poor incomes decline less than those of the non-poor, even if poverty does not decrease;
3) This definition could encourage state interventions aimed at reducing inequalities regardless of effects on economic growth.

To address these critiques, the absolute definition of pro-poor growth is used. Growth is considered pro-poor if it reduces the poverty rate in absolute terms, focusing on changes in poverty indices. Ravallion and Chen (2003) and Kraay (2004) adopt this approach and show that growth is always pro-poor as long as the income of poor individuals increases. One limitation of this definition is that it considers a scenario where economic growth coincides with rising inequality as still being pro-poor.

The theoretical review shows that no systematic relationship exists between growth, inequality, and poverty. However, it is established that the effects of growth and income distribution can interact and influence poverty reduction.

2.2 Empirical Links between Poverty, Inequality, and Economic Growth.

In recent years, several empirical studies (White and Anderson, 2000; Duclos, 2009) have examined the degree of independence or interaction between growth and income distribution to identify the transmission channels affecting poverty. Modeling the relationship between growth, inequality, and poverty is based on two complementary approaches: econometric and arithmetic.

The econometric approach estimates the elasticity of the poverty rate with respect to mean income. Using poverty decomposition into growth and inequality effects based on data from India and Brazil, Datt and Ravallion (1992) found that the growth effect largely dominates the inequality effect. Lachaud (1996) conducted a comparative analysis of the relationship between economic growth, poverty, and income inequality in three Sub-Saharan African countries and found that the poverty elasticity with respect to per capita expenditure and the Gini index is higher in urban areas than in rural areas, indicating greater social vulnerability in urban settings.

Using the basic needs approach, Fambon (2005) analyzed poverty dynamics in Cameroon and the relationship between growth, inequality, and poverty, defining two poverty lines: a "lower poverty line" of 373.26 CFA francs and an "upper poverty line" of 533.87 CFA francs. Fambon's results confirmed Lachaud's (1996) conclusions and showed that poverty increased in Cameroon due to the adverse effect of economic contraction outweighing redistribution effects, which were favorable to the poor.

Ali and Thorbecke (1998), using survey data from 16 Sub-Saharan African countries, found that rural poverty is more sensitive to growth, while urban poverty is more responsive to changes in income distribution. Applying Datt and Ravallion's (1992) method, Boccanfuso and Kaboré (2004) measured the relative contributions of growth and inequality to poverty in Burkina Faso and Senegal. They found that income redistribution in Burkina Faso between 1994 and 1998 helped reduce poverty incidence, depth, and severity, whereas in Senegal, redistribution worsened these measures.

Chen and Ravallion (1997) showed a strong relationship between income growth and poverty reduction. Their global analysis indicated a strong correlation between rising poverty and falling average income, and between declining poverty and increasing income, highlighting a robust link between per capita income growth and poverty reduction. However, the poorest populations are heterogeneous, meaning growth sensitivity may mask disparities within the poor group.

Déolalikar (2002) examined the effects of economic growth and inequality on poverty reduction in Thailand (1992–1999), finding that growth reduced poverty while inequality increased it. High inequality reduces future growth rates, thereby limiting poverty reduction. Dollar and Kraay (2000), using data from 92 countries, found that income distribution did not change significantly in favor of or against the poor, suggesting that growth is relatively neutral in terms of inequality.

Avom and Carmignani (2008) estimated a structural three-equation model considering 15 policy variables grouped into five categories: economic structure, external sector, macroeconomic framework, infrastructure, and social conditions. Their results showed significant elasticities of poverty with respect to growth and redistribution, indicating that a combination of economic growth and redistribution is the most effective strategy for poverty reduction. Growth and redistribution reinforce each other: reducing inequality promotes growth, while faster growth reduces inequality.

Econometric approaches provide insights into growth and inequality trends and their poverty implications but remain silent on transmission mechanisms. Therefore, analyzing the degree of independence or interaction between growth, inequality, and poverty is essential. The arithmetic approach, known as the Poverty-Growth-Inequality (PGI) triangle, evaluates the impact of growth and redistribution on poverty dynamics and the effectiveness of development strategies (Bourguignon, 2004). Following Datt and Ravallion (1992) and Kakwani (1993), Bourguignon decomposes poverty into growth and inequality effects. Using income distribution density, he explains that growth reduces poverty incidence as fewer individuals fall below the poverty threshold, while distributional effects reflect changes in income redistribution around the mean.

From this theoretical and empirical review, it emerges that reducing poverty depends primarily on strong economic growth and improved equality. While empirical findings differ, it is clear that growth alone is insufficient to reduce poverty, and redistributing income and assets to enhance social welfare is not necessarily harmful to growth. Empirical evidence suggests that, regardless of the nature of the links, combining economic growth with redistribution is the most favorable scenario for poverty reduction.

3. Methodological Framework

Choosing a Panel VAR Model (PVAR)

Many researchers have employed panel VAR (Vector Autoregression) models to analyze the transmission of asymmetric shocks across countries and over time. For instance, Canova et al. (2012) examined how interest rate shocks in the United States propagate to ten European economies, seven of which are in the euro area and three outside it. They also analyzed how shocks in the German economy, which increase domestic production, employment, consumption, and investment, are transmitted to nine other euro area countries.

Furthermore, Ciccarelli et al. (2012a), emphasizing the heterogeneity of macro-financial links between developed economies, compared the transmission of real and financial shocks across countries. Beetsma and Giuliodori (2011), as well as Lane and Benetrix (2011), explained the transmission of public spending shocks using panel VAR models. Boubtbane et al. (2010) examined how immigration shocks affect employment differently across countries. Finally, Love and Zicchino (2006) measured the impact of shocks on financial sectors and the cross-sectional dimension of U.S. firms.

The panel VAR model offers several advantages. Among others, it highlights the relationships between a set of variables at a given time, their lagged values, and other variables considered exogenous. Econometrically, exogenous shocks can be identified from the residuals of the estimated equations. By applying a few assumptions grounded in economic theory, these shocks can be interpreted, for instance, as fiscal policy shocks. In the context of monetary unions, a more recent approach is to use panel VAR models, as comprehensively reviewed by Canova and Ciccarelli (2013). The PVAR methodology also allows for the simulation of structural shocks- in this case, shocks arising from independent fiscal policy decisions and the macroeconomic environment- to attempt to confirm or reject a monetary or fiscal explanation of economic fluctuations (Bernanke, 1986; Blanchard and Watson, 1986; Blanchard, 1989; Blanchard and Quah, 1989).

3.1 Presentation of a PVAR Model

The distinguishing feature of VAR models is that all variables are treated as endogenous and mutually interdependent, although in some cases, exogenous variables can be incorporated (see the approach introduced by Ramey and Shapiro, 1998). Let us denote a vector of endogenous variables as YtYt. Then, the VAR model can be written in the following form:

$$Y_t = A_0(t) + A(\ell)Y_{t-1} + u_t \quad u_t \approx iid(0, \Sigma_u) \quad (7)$$

Where $A(\ell)$: is a polynomial in the lag operator; means independently and identically distributed; A_j denotes the matrix of coefficients for the imposed restrictions. To ensure the variance of Y_t is bounded and that $A(\ell)^{-1}$ exists, we assume that no root of $A(e^{-w})^{-1}$ lies on the unit circle. Sometimes the equation (1) is decomposed into short-run and long-run effects following Beveridge and Nelson (1981) and Blanchard and Quah (1989). In this thesis, that distinction is not critical since the data are panel. For this reason, we will collect $A_0(t)$ all deterministic components of the data into . Thus, one may allow representation (7) to include seasonal dummies, constants and a deterministic polynomial in time. A modification of the same equation permits the variables G in Y_t to be a linear function and W_t a set of predetermined or exogenous variables. Hence the VAR can be written in the following form:

$$Y_t = A_0(t) + A(\ell)Y_{1t-1} + F(t)W_{2t} + u_t \quad (8)$$

This method was used by Cushman and Zha (1997) to analyze the impact of monetary shocks in Canada and later by Kilian and Vega (2011) to measure how world market prices affect national economies.

According to Canova (2007), in general, fixed-coefficient VARs like equation (1) can be derived in several ways. The standard approach is to use Wold's theorem and assume linearity, stationarity, and invertibility of the resulting moving-average representation. Under these assumptions, there exists a (infinite-lag) VAR representation for any vector Y_t . However, wishing to eliminate this "infinite-lag" dimension and to use a VAR of order p in empirical analyses, we must further assume that the contribution of Y_{t-j} to Y_t is small when j is large.

Panel VARs have the same structure as simple VARs in the sense that all variables are assumed endogenous and interdependent. The difference here lies in the introduction of the cross-sectional dimension in the representation. Thus, consider Y_t as the aggregated form of y_{it}, the vector of G n endogenous variables for each country i, $i = 1,.........., N$; that is, $Y_t = (y_{1t}, y_{2t}, ...y_{Nt})$. Here the index (i) is generic and could denote countries, sectors, markets, or combinations thereof. Hence the panel VAR can be written as follows:

$$y_{it} = A_{0i}(t) + A_i(\ell)Y_{t-1} + u_{it} \quad (2)$$

avec $i = 1,......., N$; $t = 1,...........T$

where u_{it} is a vector $G \times 1$ of random effects; and $A_{0i}(t)$, A_i may depend on the country (i). Considering the general form of a panel VAR model, the representation is as follows:

$$y_{it} = A_{0i}(t) + A_i(\ell)Y_{1t-1} + F_i(\ell)W_t + u_{it} \quad (9)$$

where $u_t = [u_{1t}, u_{2t}, ...u_{NT}] = 0, \forall j \in N$ is a vector $G \times 1$ of random perturbations or innovations, that is, white noise with respective $\sigma_1^2, \sigma_2^2.........\sigma_N^2$ variances and uncorrelated; F_i are matrices $G \times M$ for each lag and W_t is a vector of dimension $M \times 1$ of predetermined or exogenous variables, common to all countries (*i*).

From the equations (8) and (9), we can deduce that a panel VAR has three characteristics: first, the lags of all endogenous variables for all countries are included in the model for country (*i*), which explains the dynamic interdependencies; second, the U_{it} are generally correlated across (*i*). Since the same variables are present in each country, there are restrictions on the covariance matrix of the shocks U_{it}: this is the principle of static interdependencies. Finally, the slope and covariance of the shocks can be unit-specific: this is cross-sectional heterogeneity. These characteristics distinguish a panel VAR commonly used in macroeconomic and financial analyses from that used in the microeconomic approach, where interdependencies are generally ignored, such as in the works of Holtz-Eakin et al. (1988) and Vidangos (2009).

In a way, a panel VAR applies in a space where dynamic and static interdependencies are allowed, even though the heterogeneity of the cross-sectional dimension imposes a restriction on the covariance matrix of the error terms.

For example, *G*, suppose there are: 3 endogenous *N* variables; 3 countries *M* and 2 exogenous variables. The panel VAR is written as follows:

$$y_{1t} = a_1 + A_{11}(\ell)y_{1t-1} + A_{12}(\ell)y_{2t-1} + A_{13}(\ell)y_{3t-1} + F_1(\ell)W_t + u_{1t} \quad (10)$$

$$y_{2t} = a_2 + A_{21}(\ell)y_{2t-1} + A_{22}(\ell)y_{2t-1} + A_{23}(\ell)y_{3t-1} + F_2(\ell)W_t + \mu_{2t} \quad (11)$$

$$y_{3t} = a_3 + A_{31}(\ell)y_{1t-1} + A_{32}(\ell)y_{2t-1} + A_{33}(\ell)y_{3t-1} + F_3(\ell)W_t + u_{3t} \quad (12)$$

$$W_t = M(\ell)W_{t-1} + w_t \quad (13)$$

$$Y_t = \begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} \quad A_{0i}(t) = \begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix} \quad A_i = \begin{pmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ A_{31} & A_{32} & A_{33} \end{pmatrix} \quad F_i = \begin{pmatrix} F_1 \\ F_2 \\ F_3 \end{pmatrix} \quad \mu_t = \begin{pmatrix} \mu_{1t} \\ \mu_{2t} \\ \mu_{3t} \end{pmatrix} \quad W_t = \begin{pmatrix} W_t \\ W_t \\ W_t \end{pmatrix}$$

In addition, $E(u_t u_t') = \sum_u \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix}$ is a full matrix and an additional structure on the matrices σ_{ij} of dimensions 5×5 with $i, j = 1,2,3$, then the variables G are the same for each country. In this case, the three characteristics of a panel VAR appear: there are dynamic $(A_{ik,j} = 0, k \neq i)$ interdependencies for For some j, there are static interdependencies $(\sigma_{i,k} \neq 0, k \neq i)$ and there are cross-sectional heterogeneities $(A_{i,k} \neq A_{i+1,k}, k \neq i, i+1)$.

However, it is evident that the three characteristics of panel VARs do not apply in all cases. For example, when analyzing the transmission of shocks across financial markets in different countries, static interdependencies are likely sufficient if the analysis period is very short (e.g., one month). Similarly, when analyzing monetary unions, it may be more important to account for slope heterogeneities (since countries may react differently to an asymmetric shock) than for variance heterogeneities (shocks affect countries to different extents). Furthermore, differences in dynamics are likely to be significant when the panel includes both developing and developed countries, or when it combines markets with different transaction volumes, different transaction costs, etc.

Several sub-models are involved in the specification, and thus certain restrictions can be tested. For example, one might want to know whether a model without dynamic interdependence is sufficient to characterize the available data. This is the configuration used when all units are small and do not exert dynamic effects on other units, but shocks in different units have a common component. This approach is generally used in some macro studies that treat units as isolated islands (Rebucci, 2010; De Greave & Karas, 2012; Sa et al., 2012). Another specific restriction within the general framework, often used in the literature, avoids all interdependencies and assumes cross-sectional slope homogeneity. This method is frequently used in micro studies but can be potentially problematic in macroeconomic analyses involving countries or regions. Even within this restricted approach, micro and macro panels share an important point: the cross-sectional dimension is generally large in micro studies and small or moderate in macro panels, and vice versa.

Analysis of shocks in dynamic panel VAR

Both Lutkepohl (2005) and Hamilton (1994) show that a VAR model is stable if all roots of the joint matrix are strictly less than 1. This matrix is represented by:

$$\overline{A} = \begin{bmatrix} A_1 & A_2 & . & A_P & A_{P-1} \\ 1_K & 0_K & . & . & 0_k \\ 0 & 1_k & 0_k & . & 0_k \\ . & . & . & . & 0_k \\ 0_k & .0_k & . & 1_k & 0_k \end{bmatrix} \quad (14)$$

Stability implies that the panel VAR is invertible and admits an infinite-order vector moving average representation, thereby facilitating the analysis of impulse responses and forecast error variance.

The impulse response function (ϕ_i) represents the effect of an innovation (or residual) shock on the current and future values of the variables specified in the model. It can be calculated by writing the model as an infinite vector moving average:

$$\phi_i = \begin{cases} I_k & i = 0 \\ \sum_{j=1}^{t} \phi_{t-j} A_j & i = 1,2 .... \end{cases} \quad (15)$$

Since innovations e_{it} are simultaneously correlated, a shock to one variable can directly affect that variable and is also transmitted to all other variables through the dynamic structure of the VAR. Suppose we have a matrix P such that $P'P = \sum$. Then, the shocks must be orthogonalized using a linear transformation matrix by multiplying the vector of canonical innovations (or canonical residuals) by a matrix previously defined as $e_{it}P^{-1}$. To transform the moving average vector parameters into impulse responses, we orthogonalize $P\phi_i$. The matrix P effectively imposes identification restrictions on the dynamic equation system. Sims (1980) proposed the Cholesky $\sum$ decomposition in to impose a recursive form on a VAR. However, the decomposition is not unique but depends on the order of the variables in $\sum$. The confidence intervals of the impulse response function can be derived analytically based on the asymptotic distribution of the panel VAR parameters and the error variance-covariance matrix. Alternatively, the confidence interval can also be estimated using Monte Carlo simulation and Bootstrap resampling methods.

Forecast error variance decomposition

There are several techniques for performing forecast error variance decomposition. In this thesis, we will use the Cholesky decomposition. Its objective is to determine, for each innovation, its contribution to the forecast error variance. As this method is the most commonly used, it requires no economic a priori, but the choice of variable order is important. Variables must be ordered from the most exogenous to the least exogenous. The forecast error can be expressed as follows:

$$y_{it+h} - E\left[y_{it+h}\right] = \sum_{i=0}^{h-1} e_{i(t+h-i)}\phi_i \quad (16)$$

Where y_{it+h} is the vector observed at time $t+h$; $E\left[y_{it+h}\right]$ is the vector predicted at time t . As with impulse response functions, the shocks are orthogonalized $e_{it}P^{-1}$ using the matrix to isolate the contribution of each variable to the forecast error variance I_k . The orthogonal shocks have a covariance matrix, which allows for a straightforward decomposition of the forecast error variance. More specifically, the contribution of a variable m to the -step-ahead forecast h error variance of variable n can be calculated as:

$$\sum_{i=0}^{h-1} \theta_{mn}^2 = \sum_{i=1}^{h-1} \left(i_n' P \phi_i i_m\right)^2 \quad (17)$$

Where i_s is the nth column of I_k . In practice, contributions are often normalized relative to the forecast deviation ahead of h of the variable n .

$$\sum_{i=0}^{h-1} \theta_n^2 = \sum_{i=1}^{h-1} i'_n \theta_i' \sum \phi_i i_n \quad (18)$$

For impulse response functions, confidence intervals can be derived analytically or estimated using various resampling techniques.

3.2 The Empirical Model

The empirical model consists of three equations. The first is the poverty equation (Pov_{it})which depends on the lagged levels p of the logarithm of GDP and inequalities represented by the Gini index.

$$Pov_{it} = \sum_{p=1}^{k} \theta_p lnPIB_{it-p} + \sum_{p=1}^{k} \mu_p Gini_{it-p} + \varepsilon_{it}$$

$$lnPIB_{it} = \sum_{p=1}^{k} \beta_p Pov_{it-p} + \sum_{p=1}^{k} \rho_p Gini_{it-p} + \pi_{it}$$

$$Gini_{it} = \sum_{p=1}^{k} \alpha_p Pov_{it-p} + \sum_{p=1}^{k} \gamma_p lnPIB_{it-p} + \vartheta_{it}$$

With

(Pov_{it}) : poverty level of country i at time t

$lnPIB_{it}$: Logarithm of the Gross Domestic Product of country i at time t

$Gini_{it}$: Gini index of country i at time t

4. Data Sources

The data comes from three sources: GDP is extracted from the World Bank's World Development Indicators (WDI) database. The poverty series comes from Povcalnet, and the Gini index is taken from the All the Ginis (ALG) dataset (version: 2025) from New York University. This dataset represents a compilation and adaptation of income or consumption Gini coefficients extracted from nine sources to create a single "normalized" Gini variable. The dataset was intentionally created in a flexible format so that each user can decide to use only one or two of these sources or combine multiple sources in a particular way. The Gini index covers the period 1950–2017 and includes 166 countries. There are over 5,000 Gini values (all from nationally representative household surveys). For our model, we use data from the period 2000–2025.

5. Presentation of Results

5.1 Optimal Lag Length

Based on the three model selection criteria defined by Andrews and Lu (2001) and the overall coefficient of determination, the first-order VAR model is the preferred model, as it has the smallest MBIC, MAIC, and MQIC values. We also aim to minimize Hansen's J statistic, but it does not correct for degrees of freedom in the model, unlike Andrews and Lu's model and moment selection criteria. Based on the selection criteria, we fitted a second-order VAR model with the same instrument specifications as above, using GMM estimation implemented by pvar.

Table 1: Optimal Lag Test

Lag	CD	J	J p value	MBIC	MAIC	MQIC
1	0,80	41,67	0,00	-28,38	5,67	-7,25
2	0,96	17,07	0,05	-17,96	-0,93	-7,39
3	0,99					

5.2 Granger Test

The results of the Granger causality tests below show that GDP and inequality Granger-cause poverty, that poverty and GDP cause inequality, and that poverty and inequality cause growth at the usual confidence levels.

Paper ID: SR26125050412 DOI: https://dx.doi.org/10.21275/SR26125050412

Table 2: Granger causality test.

Equation\ Excluded	chi2	df	Prob> chi2
Headcount			
Giniindex	12,74	2	0,00
lPIB	12,87	2	0,00
ALL	18,23	4	0,00
Giniindex			
Headcount	5,22	2	0,07
lPIB	37,66	2	0,00
ALL	46,31	4	0,00
lPIB			
Headcount	10,69	2	0,01
Giniindex	17,71	2	0,00
ALL	67,65	4	0,00

5.3 Stability Test

Regarding the VAR stability condition, the table and graph of the eigenvalues obtained confirm that the estimation is stable.

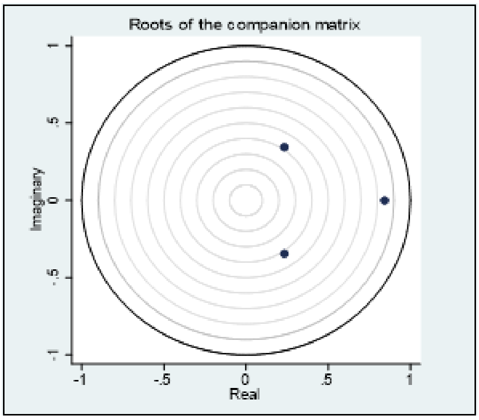

Figure 1: Stability test

5.4 Estimated Models

Three models were estimated. We compare the VAR (2) estimates and two specifications using the default options with single-lag instruments (pvar_2) by employing a two-lag "GMM"-type instrument set (pvar2_GMM). The VAR/panel VAR point estimates are summarized in a table below. Based on the point estimates and calculated standard errors, note that the 95% confidence interval for each coefficient, i.e., approximately two standard errors on either side of the point estimate, overlap between the estimators. Furthermore, pvar uses one less observation than var due to the orthogonal transformation.

PVAR model estimates are rarely interpreted on their own. We are interested in the impact of exogenous changes in each endogenous variable on other variables in the panel VAR system by estimating impulse response functions (IRFs) and forecast error variance decompositions (FEVDs).

We find that shocks to GDP have a direct impact on the Gini inequality index and on poverty intensity, while inequalities affect economic growth and poverty. Poverty intensity affects economic growth and inequalities.

Using this causal ordering, we calculated the impulse response function and decomposed the variance. The impulse response function confidence intervals are calculated using 200 Monte Carlo draws based on the estimated model. Standard errors and confidence intervals for the variance decomposition are also available.

Table 3: Econometric Estimates

	VAR			PVAR			PVAR GMM		
Variables	Pauvreté	Giniindex	lPIB	Pauvreté	Giniindex	lPIB	Pauvreté	Giniindex	lPIB
LPauvrete	-3.15*** (0.81)	0.40*** (0.01)	0.10*** (0.006)	-4.129*** (1.08)	0.661 (0.41)	-0.30*** (0.10)	-4.12*** (1.08)	0.661* (0.41)	-0.30*** (0.10)
L2.Pauvrete	4.32*** (1.04)	-0.45*** (0.015)	-0.11*** (0.007)	-0.40 (0.27)	-0.23** (0.11)	0.034 (0.023)	-0.40 (0.27)	-0.23** (0.11)	0.034 (0.023)
L.Giniindex	-23.23*** (5.46)	2.86*** (0.08)	0.66*** (0.04)	3.75*** (1.12)	1.16*** (0.38)	0.29*** (0.11)	3.75*** (1.12)	1.16*** (0.38)	0.29*** (0.11)
L2.Giniindex	23.46*** (5.10)	-1.82*** (0.07)	-0.64*** (0.03)	1.28** (0.58)	1.13*** (0.16)	0.25*** (0.06)	1.28** (0.58)	1.13*** (0.16)	0.25*** (0.06)
L.lPIB	-15.30* (8.01)	1.71*** (0.11)	1.02*** (0.06)	3.98 (3.24)	-7.32*** (1.27)	1.68*** (0.32)	-3.98** (3.24)	-7.32*** (1.27)	1.68*** (0.32)
L2.lPIB	-16.89** (8.08)	-1.77*** (0.11)	-0.09 (0.06)	-5.50*** (1.57)	-0.58 (0.69)	-0.76*** (0.17)	-5.50*** (1.57)	-0.58 (0.69)	-0.76*** (0.17)
Constant	-27.03* (14.46)	-0.38* (0.21)	0.15 (0.10)						

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

5.5 Discussion of Results

The PVAR-GMM model is used to determine the impact of the different variables in the system of equations (poverty, inequality, and growth).

5.5.1 Poverty

Lagged inequality and growth over two periods determine poverty, and the coefficients are significant at 1%, 5%, and 10%. Indeed, a 1% increase in GDP lagged by one year and two years reduces the intensity of poverty by 3.98% and 5.50%, respectively, resulting in a total decrease of 9.48%. Conversely, a 1% increase in inequality lagged by one year raises the intensity of poverty by 3.75%, while inequality lagged by two years leads to an increase of 1.28%, resulting in an overall increase of 5.03% (3.75% + 1.28%) in the intensity of poverty. A 1% shock to the intensity of poverty reduces poverty by 4.12%. Overall, the residual effect of all

Paper ID: SR26125050412 DOI: https://dx.doi.org/10.21275/SR26125050412

variables on poverty is a decrease of 0.33%. Regarding the variance decomposition of the intensity of poverty (Table), inequality and growth explain 41.80% of the variations, with a contribution of 21.47% from inequality and 20.33% from growth.

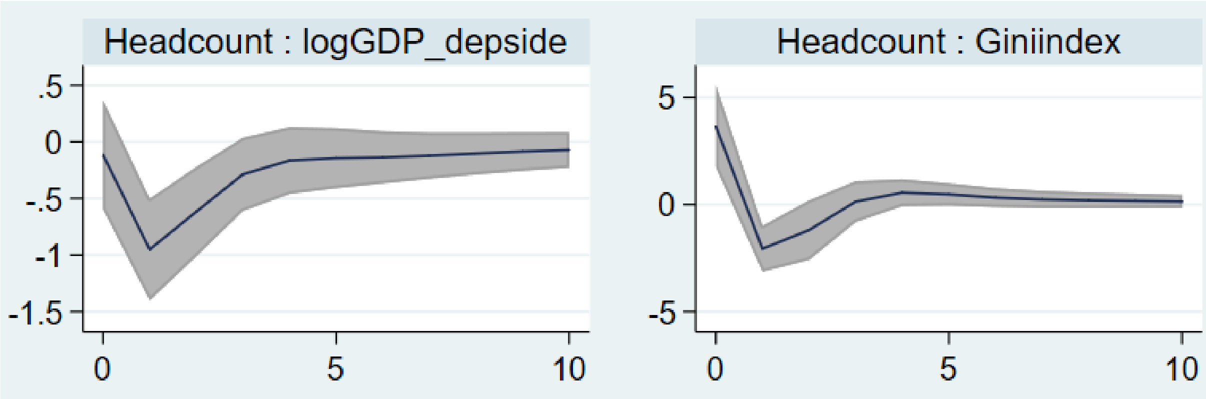

Figure 2: Impulse Response Function for Poverty

5.5.2 Inequality

Delayed poverty by two years has a negative impact on inequalities. A 1% increase in the intensity of poverty reduces inequalities by 0.23%. A 1% increase in the Gini index delayed by one year and two years increases inequalities by 1.16% and 1.13%, respectively, totaling 2.29%. GDP delayed by one year leads to a 7.32% decrease in inequalities.

Based on variance decomposition estimates (Table), we find that no less than 16.77% of the variation in inequalities can be explained by poverty and growth. Poverty contributed 5.99%, and economic growth contributed 9.68%.

In terms of levels, the IRF graph shows that a positive shock to inequalities leads to a short-term decrease in GDP and a long-term increase. A shock to inequalities results in a decrease in the intensity of poverty for four years before the effect begins to dissipate.

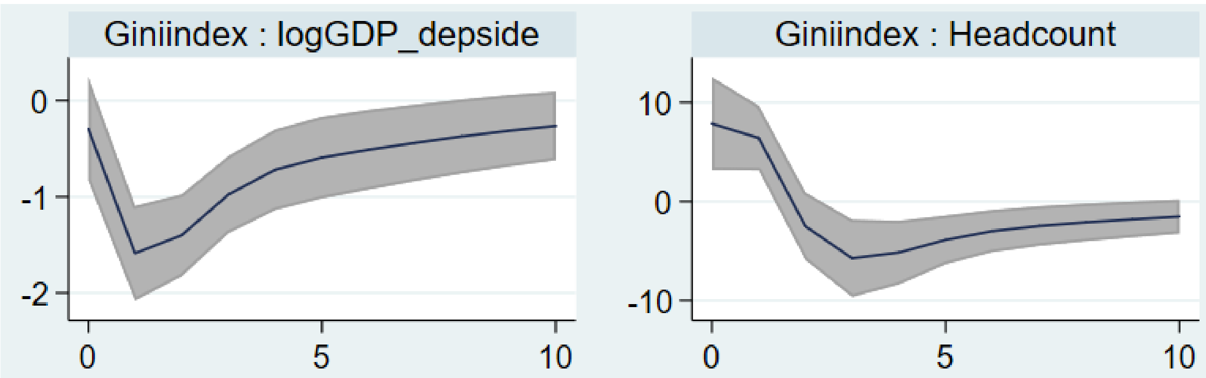

Figure 3: Impulse Response Function for Inequality

5.5.3 Growth

The intensity of poverty negatively affects economic growth. A 1% increase in the intensity of poverty, lagged by one year, reduces growth by 0.30%. An increase in the Gini index, lagged by one and two years, increases economic growth by 0.29% and 0.25%, respectively, resulting in a total increase of 0.54%. An increase in economic growth lagged by one year leads to a 1.68% rise in economic growth, while a two-year lag in GDP results in a 0.76% decline, leaving a residual increase of 0.92%.

Regarding the variance decomposition of growth, variations in growth are attributed to inequalities and poverty by 39.84%. Poverty contributes minimally to GDP variations, accounting for only 1.73%, while inequalities account for 38.15%.

A shock to GDP reduces inequalities in the short term (2 years). Starting from the third year, an increase in economic growth is observed before the effect dissipates after 10 years. In the long term, a shock to GDP leads to a reduction in poverty.

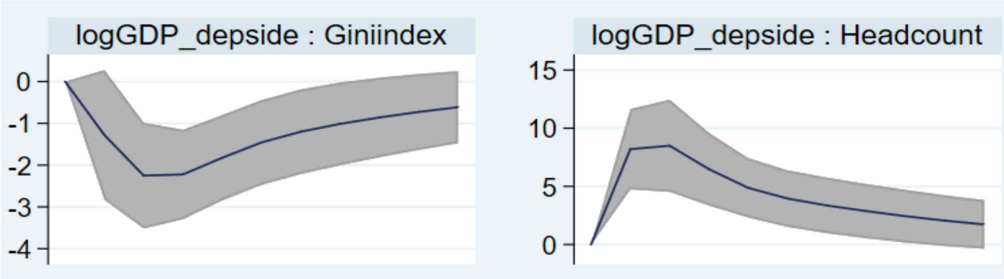

Figure 4: GDP Impulse Response Function

6. General Conclusion

The primary objective of this study was to establish and analyze the dynamic links between poverty, inequality, and economic growth in Senegal, using a Panel Vector Autoregression (PVAR) model for the period 2000-2025. The empirical results confirm the existence of significant and complex interactions between these three variables, shedding light on the mechanisms through which growth and redistribution influence the evolution of poverty.

On the one hand, the analysis shows that an increase in lagged GDP by one and two years leads to a significant reduction in the intensity of poverty, thus confirming the crucial role of economic growth in the fight against poverty. However, this growth is also accompanied by differentiated effects on inequalities: in the short term, an increase in GDP contributes to reducing inequalities, but they can subsequently rise in the long term if redistributive mechanisms are not activated. On the other hand, inequalities, measured by the Gini index, exert a negative impact on both growth and poverty. An increase in inequalities raises the intensity of poverty and hampers future growth, thus highlighting the self-reinforcing nature of inequalities.

Impulse response functions and forecast error variance decompositions helped clarify the nature and persistence of shocks. A positive shock on growth reduces poverty in the long term, but its effect on inequalities is more ambiguous, with an initial decline followed by a rebound. Conversely, a shock on inequalities negatively and durably affects both growth and poverty. These results validate the hypothesis that growth alone is not sufficient to guarantee a sustainable reduction in poverty; it must be accompanied by active redistribution policies to correct imbalances and amplify the positive effects on the well-being of the most vulnerable populations.

From a methodological standpoint, the use of the PVAR-GMM model made it possible to capture dynamic and static interdependencies between countries and variables, while controlling for cross-sectional heterogeneity. Granger causality tests confirm bidirectional causal relationships between poverty, inequality, and growth, reinforcing the relevance of a systemic approach for analyzing these phenomena.

In terms of economic policies, this study argues in favor of an integrated approach combining growth stimulation and inequality reduction. For Senegal, where the poverty rate remains high despite the efforts of recent decades, it is imperative to implement structural policies aimed at improving access to basic services, strengthening financial inclusion, supporting sectors with high employment potential, and correcting spatial and social disparities. So-called "pro-poor" growth must not only increase average income but also improve its distribution, specifically targeting the most disadvantaged groups.

The limitations of this study, particularly related to data availability, the analysis period, and methodological choices (such as lag order and shock identification), open avenues for future research. It would be relevant to extend the analysis to a panel of Sub-Saharan African countries, to integrate additional variables such as social spending, education, or governance, and to use more advanced structural identification methods to refine the analysis of transmission channels.

This research contributes to a better understanding of the dynamics linking poverty, inequality, and growth in Senegal. It confirms that the success of development strategies, particularly within the framework of the Emerging Senegal Plan, depends on the ability to combine economic efficiency and social equity. Only inclusive growth, supported by targeted and sustainable redistributive policies, can lead to a significant and lasting reduction in poverty and inequalities.

References

[1] Ali A. A.G et Thorbecke, E. (1998) , “Poverty in sub-saharan Africa”, Magnitude and Characteristics » *AERC, Nairobi*
[2] Avom et Carmignani, (2008): “Pauvreté, Croissance et Redistribution ”. *Revue française d’économie . Volume 13, Numéro 23-1.*
[3] Baulch, B.et M C. Culloch, (1999) “racking Pro-Poor Growth: New Ways to Spot the Biases and Benefits” 21 Insights dieses 31, September, Institute *of development Studies*.
[4] Barro, R.J. (1999) “Inequality Growth, and Investment” NBERWorking Paper 7038
[5] Bigsten A.et Levin J. (2001) “Growth, Income Distribution and Poverty”, *A Review Paper for the WIDER conference on Growth and Poverty, Helsinki, 25-26 May*
[6] Boccanfuso D.et T. S. Kaboré, (2004) : “ Croissance, inégalité et Pauvreté dans les années quatre–vingt-dix au Burkina Faso et au Sénégal”, *Revue d’économie du développement*, 2004/2vol 18 p-9 -35
[7] Boccanfuso, D. et Ménard. (2009) : « La croissance pro-pauvre : un aperçu exhaustif de la boite à outils » *GREDI, Working* paper 09-06

[8] Chen, S. et M. Ravallion, (1997): "What Can New Survey Data Tell Us about Recent Changes in Distribution and Poverty?", Word Bank Research Observer, 11
[9] Chen, S. et M. Ravallion, (2003): "Measuring Pro-Poor Growth", Word Bank, Policy Research Working Paper dieses 2666
[10] Datt, G.et M. Ravallion, (1992): "Growth and redistribution components of charges in poverty measures: A decomposition with application to Brazil and India in the 1980's", *Journal of development economics*° 83 ,275 -295
[11] Deolalikar, A. B, (2002): "Poverty, Growth and Inequality in Thailand", *Asian Development Bank* WERD Working Paper n°8
[12] Dollar, D.et A. Kraay, (2002): "Growth is good for the poor", *Journal of Economic Growth, Vol* 7, pp195-225
[13] Duclos, J.-Y., (2009): "What is Pro-poor?", *Social Choice and Welfare* Vol 32, pp 37-58
[14] Fambon, S. (2005): "Croissance économique, pauvreté et inégalité des revenus au Cameroun" *Revue d'économie du développement*, 2005/1 vol 19, p 91-122
[15] Foster, J.E., J. Greer et E. Thorbecke, (1984): "A class of decomposable Poverty measures", Econometrica, 52,pp761-766.
[16] Galor, O. et J. Zeira, (1993): "Income Distribution and Macroeconomics" *Review of economic Studies, 60*: 35-52
[17] Goudie et Ladd, (1999): "Economics growth, poverty and Inequality "*Journal of international development*, volume 11, issues 2, page 177-195.
[18] Kakwani. (1993): "Poverty and Economic Growth with Application to Côte d'Ivoire "*Review of Income and Wealth*; 39, pp 121-139
[19] Kakwani, N.et E.Pernia, (2001): "What is Pro-Poor Growth?" *Asian Development Review*, 18, pp 1-16
[20] Kakwani, N.et H. Son, (2002): "Pro-Poor Growth: concept, Measurement, and Application", unpublished mimeo, university of New South Wales, Sydney
[21] Klasen, S. (2002): "In search of the Holy Grail. How to achieve Pro-Poor Growth" Papier présenté à la conference ABCDE-Europe organisée par la Banque Mondiale, Oslo, 24-26 juin
[22] Kraay (2004): "Trade, growth and Povery". The Economic Journal, 114 (February), F22–F49
[23] Kuznets, S. (1955):" Economic Growth and Income Inequality" in the *American Economic Review, XLV, 1* March (1955), 65, P.1-28
[24] Lachaud J.P (1996) : "Pauvreté, vulnérabilité et marché du travail au Burkina Faso, groupe d'économie du développement de l'Université Montesquieu Bordeaux IV
[25] Persson, T.et G.Tabellini,(1994): "Is inequality Harmful for Growth?" *American Economic Review, 84*(3):600-621
[26] Shapley, L. (1953): A value for n-person games, in: "H. W. Kuhn and A. W. Tucker, eds., Contributions to the Theory of Games", Vol. 2 (Princeton University Press).
[27] Shleifer, A.et R. W. Vishny, (1998): "Income Distribution, Market Size, and Industrialization."Quaterly Journal of Economics: 537-64, août
[28] Shorrocks, A.F.; (1999): Decomposition Procedures for Distributional Analysis : "A Unified
[29] Framework Based on the Shapley Value. Mimeo". Department of Economics, University of Essex.
[30] Shorrocks, A.F.; Kolenikov, S., 2001: "Poverty Trends in Russia During the Transition". Mimeo.
[31] Stiglitz, J.E., (1969): "Distribution of Income and Wealth among Individuals" Econometrica, 37(3): 382-397
[32] White, H.et E. Anderson, (2000): "Growth Vs Redistribution: Does the pattern of Growth Matter?", Institute of Development Studies, University of Sussex.

Author Profile

Mbaye AW holds a Doctorate in Economic Sciences from Cheikh Anta Diop University of Dakar, graduating in 2021. He works as a consultant in strategy and financial engineering, notably for the IFECA firm, and as a consultant for Senegal's General Inspectorate of Finance and the Universal Competences Consulting firm. Academically, he has been a teacher-researcher at the Dakar Institute of Management (ISM) since 2005 and a lecturer at Cheikh Anta Diop University and at Alune Diop University. He teaches various modules in economics, finance, project management, and maritime economics. His areas of expertise include foresight studies, corporate governance, business valuation, financial and economic analysis. He is the author of scientific publications, including his thesis on governance, institutions, and economic growth in West Africa. He also participates in training missions and studies for national institutions.

Annexes.

	Gini			Poverty			GDP		
Horizon	Gini	Poverty	logPIB	Gini	Poverty	logGDP	Gini	Poverty	logGDP
0	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
1	100,00%	0,00%	0,00%	13,56%	86,44%	0,00%	1,78%	0,13%	98,08%
2	93,10%	5,58%	1,32%	16,27%	74,26%	9,47%	26,98%	2,23%	70,80%
3	88,83%	6,59%	4,58%	15,85%	67,83%	16,32%	35,07%	1,93%	63,00%
4	86,56%	6,39%	7,06%	18,45%	63,10%	18,46%	37,03%	1,81%	61,16%
5	85,50%	6,21%	8,29%	20,12%	60,68%	19,20%	37,52%	1,79%	60,68%
6	84,99%	6,10%	8,90%	20,80%	59,55%	19,64%	37,75%	1,77%	60,48%
7	84,70%	6,05%	9,25%	21,11%	58,95%	19,94%	37,92%	1,75%	60,33%
8	84,51%	6,02%	9,47%	21,28%	58,58%	20,14%	38,03%	1,74%	60,23%
9	84,40%	6,00%	9,60%	21,40%	58,35%	20,26%	38,11%	1,73%	60,16%
10	84,33%	5,99%	9,68%	21,47%	58,21%	20,33%	38,15%	1,73%	60,12%

Paper ID: SR26125050412 DOI: https://dx.doi.org/10.21275/SR26125050412