How does per capita income growth affect bipolar and depression disorders in Africa?

Mustapha Immurana, Kwame Godsway Kisseih, Ibrahim Abdullahi, Muniru Azuug, Ayisha Mohammed and Toby Joseph Mathew Kizhakkekara

(Information about the authors can be found at the end of this article.)

Abstract

Purpose – *Bipolar and depression disorders are some of the most common mental health disorders affecting millions of people in low-and middle-income countries, including those in Africa. These disorders are therefore major contributors to the burden of diseases and disability. While an enhancement in income is seen as a major approach towards reducing the burden of these disorders, empirical evidence to support this view in the African context is lacking. This study therefore aims to examine the effect of per capita income growth on bipolar and depression disorders across African countries.*

Design/methodology/approach – *The study uses data from secondary sources comprising 42 African countries over the period, 2002–2019, to achieve its objective. The prevalence of bipolar and major depressive disorders (depression) are used as the dependent variables, while per capita income growth is used as the main independent variable. The system Generalised Method of Moments regression is used as the estimation technique.*

Findings – *In the baseline, the authors find per capita income growth to be associated with a reduction in the prevalence of bipolar (coefficient: -0.001, $p < 0.01$) and depression (coefficient: -0.001, $p < 0.1$) in the short-term. Similarly, in the long-term, per capita income growth is found to have negative association with the prevalence of bipolar (coefficient: -0.059, $p < 0.01$) and depression (coefficient: -0.035, $p < 0.1$). The results are similar after robustness checks.*

Originality/value – *This study attempts at providing the first empirical evidence of the effect of per capita income growth on bipolar and depression disorders across several African countries.*

Keywords *Bipolar, Depression, Per capita income growth, Economic growth, Africa*

Paper type *Research paper*

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1. Introduction

Mental health is a basic human right and an essential aspect of overall well-being (including health) (World Health Organization, 2023). However, mental health conditions such as bipolar and depression disorders are major public health problems in the world (including low-and middle-income settings such as Africa). In 2019, bipolar and depression disorders affected approximately, 40 million and 280 million people in the world, respectively (Global Burden of Disease Collaborative Network, 2020a). These mental health disorders are associated with poor concentration, hopelessness, distorted sleep, low-self-worth, loss of interest in activities and increased risk of suicide, making them major contributors of disease burden and disability. Moreover, people affected by severe mental disorders die prematurely (10-20 years early) (World Health Organization, 2024).

In Africa, the situation is not different as bipolar and depression disorders are major causes of disability. For instance, in 2019, the years lived with disability associated with bipolar and major depressive disorders in sub-Saharan Africa were 1,104,403 years and 5,172,453 years, respectively (Global Burden of Disease Collaborative Network, 2020b).

Based on the human capital model of demand for health, theoretically, mental health is expected to improve as economic growth or income increases (see Grossman, 2000). Thus, rising income would enhance people's ability to afford health inputs including quality healthcare (Immurana, 2021a), as well as reduce psychosocial stress (a major risk factor of mental illnesses) by providing financial security or reducing financial stress (Golberstein, 2015). Conversely, economic growth is likely to be associated with rising competition among firms (Cherif *et al.*, 2020), which may put workers under intense pressure and stress to meet the demands of their employers. These could lead to bad mental health outcomes. For instance, stressful life events have been found to precede relapse in bipolar patients (Lex *et al.*, 2017) as well as associated with initial episodes of depression disorders (Monroe *et al.*, 2019).

On the empirical front, while a number of studies have examined the association between income and mental health disorders (Golberstein, 2015; Green *et al.*, 2016; Haushofer and Shapiro, 2016; He *et al.*, 2021; Hjelm *et al.*, 2017; Kilburn *et al.*, 2018; Pega *et al.*, 2022; Pieh *et al.*, 2020; Powell-Jackson *et al.*, 2016; Sareen *et al.*, 2011; Shields-Zeeman *et al.*, 2021; Tachibana *et al.*, 2019; Thomson *et al.*, 2022), to the best of our knowledge, no study has examined the effect of income on bipolar and depression disorders across several African countries. Meanwhile, conducting international studies over a number of years enhances the precision of the inferences made from parameter estimates as well as aids in avoiding omitted variables bias (Hsiao, 2007).

Given that African countries have achieved per capita income growth in recent times [For instance, in sub-Saharan Africa, per capita income growth were 2.23%, 2.04% and 0.10% in 2013, 2014 and 2015, respectively (World Bank, 2023)], and income growth could positively or negatively affect mental health, it is important to examine if the realisation of per capita income growth has contributed to a reduction in the prevalence of bipolar and depression disorders on the continent. This study therefore attempts at providing the first empirical evidence of the effect of per capita income growth on bipolar and depression disorders across several African countries. From a health policy perspective, the findings are expected to highlight how an improvement in income can be used as an instrument towards reducing the prevalence of these mental health disorders and thus aid in achieving the Sustainable Development Goal 3.4 (promote mental health and well-being among others) (World Health Organization (Europe), 2023).

The remainder of the paper is structured into four sections as follows: Section 2 covers the methods, which is followed by the results in Section 3. Section 4 is devoted to the discussion, and Section 5 covers conclusion.

2. Methods

2.1 Study design

The study uses a panel design made up of 42 African countries (Appendix) with data covering the period 2002–2019. The study period and the number of countries are largely determined by data availability. The panel design is chosen given the number of years and the number of countries involved in the study.

2.2 Variables description, data sources and expected signs

In this study, the annual percentage point prevalence of bipolar disorder (bipolar [BP]) and major depressive disorder (depression [DP]) among all age groups are used as the dependent variables. The prevalence of the dependent variables are used because, unlike incidence rates which cover only new cases of a disease, prevalence covers all cases and hence gives a broader indication of the proportion of a population that is affected by a disease (Dovetail Editorial Team, 2024). The main independent variable is per capita income growth (PCI) measured as the annual growth rate of gross domestic product (GDP) per capita. The control variables used in the baseline analysis are health expenditure (CHE, measured as annual current health expenditure as a percentage of GDP), population growth (PG, measured as the annual rate of growth in the number of all residents in a country irrespective of legal status) and physician density (PD, measured as the annual number of physicians per 1,000 people). For robustness purposes, we use public health expenditure (PHE, measured as local government health expenditure as a percentage of GDP), out-of-pocket health expenditure (OOP, measured as a percentage of current health expenditure) and interpersonal violence (IPV, measured as annual percentage point prevalence among all age groups) as additional control variables. These control variables are selected based on literature (Arshad *et al.*, 2021; Arthur and Oaikhenan, 2017; Immurana, 2021a; Nketiah-Amponsah, 2019; Novignon and Lawanson, 2017; Ziaei and Hammarström, 2023). The aforementioned studies (except Ziaei and Hammarström, 2023) are chosen to select the control variables because they used macrolevel analysis which is similar to the present study. A summary of these studies can be found in the Appendix.

The data on bipolar and depression as well as interpersonal violence are obtained from the Institute for Health Metrics and Evaluation's Global Burden of Diseases Study (GBD) database (Global Burden of Disease Collaborative Network, 2020c), while data on all the remaining variables are obtained from the database of the World Bank's World Development Indicators (WDI) (World Bank, 2023). The GBD, in particular, remains the most detailed and largest scientific attempt carried out to quantify trends and levels in health. It is conducted in collaboration with more than 9,000 researchers in over 160 countries and territories. The GBD provides an avenue to compare the immensity of risk factors, injuries and diseases across regions, countries, age groups, sexes and time (Institute for Health Metrics and Evaluation, 2023). The GBD currently covers 369 injuries and diseases in 204 territories and countries. The process of estimating the GBD is premised on several essential data sources for each injury or disease including household surveys, disease registries, censuses, health service use, vital statistics and civil registration, satellite imaging, air pollution monitors, disease notifications among others (Vos *et al.*, 2020).

The GBD estimates adhere to the Guidelines for Accurate and Transparent Health Estimates Reporting (GATHER) by making available online (i.e Global Health Data Exchange [GHDx]), a catalogue for all sources used, releasing the documentation associated with each source and posting the code associated with each step used in the analysis (Murray and Lopez, 2017). It is therefore not surprising that, over the 2000–2019 period, the World Health Organization used GBD data among others for country-level causes of death (Cao *et al.*, 2020). More detailed description of the GBD methods can be found elsewhere (Institute for Health Metrics and Evaluation, 2023; Vos *et al.*, 2020).

Regarding the expected signs of the variables, based on the human capital model of demand for health (Grossman, 2000), we expect per capita income growth to have negative association with the prevalence of bipolar and depression (i.e. although the contrary may hold, in the case of Africa, we expect the benefits of per capita income growth to outweigh its disadvantages as a number of African societies are communal in nature). Thus, growth in per capita income would increase peoples' ability to afford quality health care as well as other health inputs (Immurana, 2021a). Moreover, rising income can decrease the psychological difficulties people go through (Golberstein, 2015) as a result of inability to afford the basic necessities of life, which has the potential to worsen mental health. In the same vein, a rise in current health expenditure (as well as public health expenditure and out-of-pocket health expenditure) implies a rise in demand for health-related goods and services, which can enhance mental health (see Grossman, 2000). We therefore expect all the health expenditure indicators to have a negative association with the chosen mental health disorders. The expected effect of population growth is uncertain. This is because, while on one hand population growth could be associated with higher investment in the health sector which would enhance access to quality healthcare resulting in better health (including mental health) (Immurana, 2021a), on the other hand, population growth could put pressure on people, especially the young ones as they have to compete for the relatively few available opportunities such as jobs, which has the potential to negatively affect their mental health, especially those who will not get such opportunities (British Council, 2018; Sankoh *et al.*, 2018). An increase in the number of physicians is expected to enhance access to quality medical care, hence leading to better mental health outcomes (see Immurana, 2021a). Given that victims of interpersonal violence are likely to have psychological challenges, we expect a positive association between interpersonal violence, and bipolar and depression disorders (see Ziaei and Hammarström, 2023).

2.3 Models

The theoretical basis of this study stems from the human capital model of demand for health (Grossman, 2000) which posits that individuals are the producers of health (bipolar and depression in the case of this study) through the consumption of health inputs (health care, nutritious diets, improved water among others). A major proposition of the model is that, income growth will increase the ability of individuals to afford health inputs to produce health. Thus, income, is a major determinant of health. Therefore, to investigate the effect of per capita income growth on the prevalence of bipolar and depression, based on the human capital model of demand for health (Grossman, 2000), we specify the equations below:

$$\mathrm{BP} = f(\mathrm{PCI}, \quad \mathrm{X}) \tag{1}$$

$$\mathrm{DP} = f(\mathrm{PCI}, \quad \mathrm{X}) \tag{2}$$

where equations (1) and (2) express bipolar and depression, respectively, as functions of per capita income growth and the control variables (X), and all other notations are as defined already in Section 2.2. However, we respecify equations (1) and (2) in a more estimable form as follows:

$$\mathrm{BP}_{\mathrm{it}} = \Xi + \Omega\mathrm{BP}_{\mathrm{it}-1} + \vartheta\mathrm{PCI}_{\mathrm{it}} + \delta\mathrm{X}_{\mathrm{it}} + \Upsilon_{\mathrm{t}} + \omega_{\mathrm{it}} \tag{3}$$

$$\mathrm{DP}_{\mathrm{it}} = \Xi + \Omega\mathrm{DP}_{\mathrm{it}-1} + \vartheta\mathrm{PCI}_{\mathrm{it}} + \delta\mathrm{X}_{\mathrm{it}} + \Upsilon_{\mathrm{t}} + \omega_{\mathrm{it}} \tag{4}$$

where, Ξ, t, i, Υ and ω represent the intercept of the equations, time (years), countries, year dummies (time fixed effects) and the error term, respectively. The first lags of the dependent variables ($\mathrm{BP}_{\mathrm{it}-1}$ and $\mathrm{DP}_{\mathrm{it}-1}$) are introduced in equations (3) and (4) to make them dynamic models and also to capture the persistence of the dependent variables overtime (Immurana *et al.*, 2021a, 2021c, 2023a). The coefficients of the right-hand side variables are represented by their respective notations (Ω, ϑ, δ).

2.4 Statistical analysis

The dynamic nature of our models [equations (3) and (4)], makes estimation techniques such as the ordinary least square, fixed effects and the random effects regression models inappropriate given the likelihood of the dynamic (persistence) term correlating with the error term, creating endogeneity, which these estimation techniques are unable to deal with (Egyir *et al.*, 2020; Greene, 2012). In addition, there is the likelihood of reverse causality between the dependent variables and the independent variables including the control variables especially per capita income growth, which if not dealt with, would lead to biased estimates. For instance, rising mental health disorders can decrease the participation of people in economic activities which will reduce per capita income growth.

Given the aforementioned estimation concerns, we use the system Generalised Method of Moments (GMM) regression of Arellano and Bover (1995) and Blundell and Bond (1998) as our empirical estimation technique. This is because, aside from being dynamic in nature, the system GMM is capable of dealing with endogeneity using first differenced and level equations as well as the lags of independent variables as instruments (Immurana *et al.*, 2021b, 2023b; Roodman, 2009; Sakyi and Egyir, 2017). The statistical appropriateness of the system GMM estimates is confirmed using the Hansen overidentification test (Hansen *j*), the Arellano–Bond second-order serial correlation test (ARB) and avoiding the proliferation of instruments. The insignificance of the Hansen *j* and ARB indicates the absence of overidentification and second-order serial correlation respectively (Immurana *et al.*, 2021e, 2021d; Roodman, 2009). Also, the number of instruments being less than the number of groups/countries confirms the absence of the proliferation of instruments (Roodman, 2009). As equations (3) and (4) are short-term models, we use the Papke and Wooldridge (2005) technique to arrive at long-term estimates using the "nlcom" routine in Stata. The short-term and long-term refer to the instantaneous and cumulative (overtime) effects of the independent variables on the dependent variables, respectively (Hardy, 2018).

Moreover, to curb the proliferation of instruments, make our data more appropriate for long-term analysis, as well as reduce divergence normally linked with high frequency data and control for variations in the business cycle (Roodman, 2009; Sala and Trivín, 2014; Uprety, 2019), we take three-year averages of all variables before conducting the system GMM as well as all other analyses in this study. Last but not the least, we take logarithms (Log) of the dependent variables (in both the baseline and robustness checks) as well as public health expenditure, out-of-pocket health expenditure and interpersonal violence (in the robustness checks) to reduce the differences in the measurements of variables (Gujarati and Porter, 2009). Before the system GMM estimates, we conduct descriptive and correlation analyses as well as use the variance inflation factor (VIF) to examine the existence of multicollinearity among the independent variables. All the analyses in this study are carried out using Stata version 14.0.

3. Results

In this section, we present the descriptive statistics of the variables, matrix of correlations and the system GMM regression estimates of the effect of per capita income growth on bipolar and depression disorders in the selected African countries.

3.1 Descriptive statistics

In Table 1, the descriptive statistics show that among the sampled countries, over the study period, the average point prevalence of bipolar and depression disorders are 0.005% and 0.026%, respectively. The average growth rate of per capita income is 1.908%.

The average current health expenditure as a percentage of GDP, population growth rate and physician density are 4.961%, 2.455% and 0.328 per 1,000 population, respectively (Table 1). The descriptive statistics of the remaining variables can be found in Table 1.

3.2 Correlation among variables

In Tables 2 and 3, the correlation coefficients among the independent variables are generally low; hence, it is not surprising that the VIF results (which are available upon request) confirm the absence of multicollinearity in all our estimates. Moreover, the signs of the correlation between per capita income growth, and bipolar and depression disorders are negative as expected.

Table 1 Descriptive statistics

Variables	*Obs*	*Mean*	*SD*	*Min*	*Max*
Bipolar	252	0.005	0.001	0.004	0.009
Depression	252	0.026	0.008	0.014	0.045
Per capita income growth	248	1.908	3.331	−11.181	18.213
Health expenditure	250	4.961	2.078	1.53	18.889
Population growth	252	2.455	0.935	−0.236	4.762
Physician density	189	0.328	0.462	0.018	2.472
Interpersonal violence	252	0.033	0.007	0.018	0.056
Public health expenditure	250	1.651	1.111	0.159	5.204
Out-of-pocket health expenditure	250	41.789	18.615	3.073	83.008

Note: After averaging the data, the complete observations for variables should have been 252. Thus, variables with observations below 252 have data missing for some countries
Sources: Authors' computation using data from the GBD and WDI databases

Table 2 Matrix of correlations (baseline variables)

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
(1) Bipolar	1.000					
(2) Depression	0.554	1.000				
(3) Per capita income growth	−0.016	−0.005	1.000			
(4) Health expenditure	0.162	−0.047	0.068	1.000		
(5) Population growth	−0.394	−0.216	−0.024	−0.192	1.000	
(6) Physician density	0.342	0.183	0.023	0.081	−0.676	1.000

Note: Bipolar and depression indicators are log-transformed
Sources: Authors' computation using data from the GBD and WDI databases

Table 3 Matrix of correlations (robustness checks variables)

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
(1) Bipolar	1.000							
(2) Depression	0.554	1.000						
(3) Per capita income growth	−0.016	−0.005	1.000					
(4) Public health expenditure	0.429	0.134	0.000	1.000				
(5) Out-of-pocket health expenditure	−0.192	−0.086	0.059	−0.580	1.000			
(6) Interpersonal violence	0.252	0.240	0.038	0.264	−0.151	1.000		
(7) Population growth	−0.394	−0.216	−0.024	−0.524	0.204	−0.227	1.000	
(8) Physician density	0.342	0.183	0.023	0.502	−0.108	0.248	−0.676	1.000

Note: Bipolar, depression, health expenditure and interpersonal violence indicators are log-transformed
Sources: Authors' computation using data from the GBD and WDI databases

3.3 Regression results

This sub-section presents the short-and long-term system GMM regression results of the effect of per capita income growth on bipolar and depression disorders in the 42 selected African countries over the period 2002–2019 (Tables 4–7). In interpreting the regression results, 1%(***), 5%(**) and 10%(*) levels of significant represent p-values of less than 0.01, 0.05 and 0.1, respectively. Moreover, a positive association implies when the independent variable increases, it is associated with an increase in the dependent variable while a negative association implies, when the independent variable increases, it is associated with a fall in the dependent variable.

Table 4 Baseline short-term two-step system GMM estimates of the effect of per capita income growth on bipolar and depression disorders

	Bipolar	*Depression*
L.Bipolar	0.9791*** (0.0070)	
Per capita income growth	−0.0012*** (0.0002)	−0.0010* (0.0006)
Health expenditure	−0.0021** (0.0008)	−0.0008 (0.0027)
Population growth	−0.0184*** (0.0027)	−0.0268*** (0.0046)
Physician density	−0.0215*** (0.0034)	−0.0207*** (0.0044)
L.Depression		0.9705*** (0.0084)
Constant	−0.0320 (0.0317)	−0.0112 (0.0309)
Observations	145	145
No. of groups	42	42
No. of instruments	35	22
ARB test	−0.4523	−1.6419
ARB test *p*-value	0.6511	0.1006
Hansen *j*	32.7000	10.0479
Hansen *j* *p*-value	0.1710	0.6900
F-stat.	33,571.7069	4,092.2117
F-stat. *p*-value	0.0000	0.0000

Notes: Standard errors in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; ARB test = Arellano–Bond second-order serial correlation test; Hansen *j* = Hansen overidentification test; L. = first lag; Bipolar and depression indicators are log-transformed; for brevity, year dummies are not reported
Source: Authors' computation using data from the GBD and WDI databases

Table 5 Baseline long-term two-step system GMM estimates of the effect of per capita income growth on bipolar and depression disorders

	Bipolar	*Depression*
Per capita income growth	−0.0593*** (0.0137)	−0.0347* (0.0201)
Health expenditure	−0.1020** (0.0503)	−0.0262 (0.0914)
Population growth	−0.8824*** (0.2121)	−0.9098*** (0.1934)
Physician density	−1.0310*** (0.2247)	−0.7044*** (0.1727)
Constant	−1.5291 (1.0329)	−0.3791 (0.9681)
Observations	145	145

Notes: Standard errors in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; Bipolar and depression indicators are log-transformed
Source: Authors' computation using data from the GBD and WDI databases

3.3.1 Baseline results. In the baseline, regarding the short-term results (Table 4), we find the first lags of the prevalence of bipolar and depression to have positive significant association (coefficient: 0.979, $p < 0.01$; coefficient: 0.971, $p < 0.01$, respectively) with the current prevalence levels of bipolar and depression.

Regarding the main variable of interest; per capita income growth, we find it to have a negative significant association with the prevalence of bipolar disorder (coefficient: −0.001, $p < 0.01$). In a similar fashion, we find per capita income growth to have a negative significant association with the prevalence of depression disorder (coefficient: −0.001, $p < 0.1$) (Table 4). As the dependent variables are log-transformed and the independent variables are not, to interpret the results as elasticities, we have to exponentiate the coefficients, subtract one from the results of the exponentiation and afterwards multiply by 100 (UCLA: Statistical Consulting Group, 2023).

Regarding the control variables, we find health expenditure to have a negative significant association with the prevalence of bipolar disorder (coefficient: −0.002, $p < 0.05$). Nonetheless, with regard to the prevalence of depression disorder, although health

Table 6	Robustness short-term two-step system GMM estimates of the effect of per capita income growth on bipolar and depression disorders			
	Bipolar	*Depression*	*Bipolar*	*Depression*
L.Bipolar	0.9728*** (0.0082)		0.9931*** (0.0048)	
Per capita income growth	−0.0014*** (0.0003)	−0.0011** (0.0005)	−0.0010*** (0.0003)	−0.0024*** (0.0008)
Public health expenditure	−0.0089*** (0.0032)	−0.0082 (0.0074)	−0.0040* (0.0023)	−0.0069 (0.0072)
Out-of-pocket health expenditure	−0.0203*** (0.0024)	−0.0560*** (0.0075)	−0.0004 (0.0031)	−0.0637*** (0.0148)
Population growth	−0.0171*** (0.0024)	−0.0244*** (0.0049)	−0.0093*** (0.0024)	−0.0247*** (0.0039)
Physician density	−0.0165*** (0.0022)	−0.0249*** (0.0058)	−0.0128*** (0.0029)	−0.0612*** (0.0193)
L.Depression		0.9460*** (0.0152)		0.9406*** (0.0221)
Interpersonal violence			0.0644*** (0.0079)	0.0458 (0.0622)
Constant	−0.0052 (0.0391)	0.0884 (0.0591)	0.2290*** (0.0371)	0.2601* (0.1368)
Observations	145	145	145	145
No. of groups	42	42	42	42
No. of instruments	35	33	35	35
ARB test	1.0439	−1.6080	0.0167	−1.2622
ARB test *p*-value	0.2965	0.1078	0.9866	0.2069
Hansen *j*	28.0618	23.4395	27.2568	29.7227
Hansen *j p*-value	0.3050	0.3773	0.2926	0.1941
F-stat.	5,929.6082	1,383.3705	172,836.6729	771.2421
F-stat. p-value	0.0000	0.0000	0.0000	0.0000

Notes: Standard errors in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; ARB test = Arellano–Bond second-order serial correlation test; Hansen *j* = Hansen overidentification test; L. = first lag; Bipolar, depression, health expenditure and interpersonal violence indicators are log-transformed. For brevity, year dummies are not reported
Source: Authors' computation using data from the GBD and WDI databases

Table 7	Robustness long-term two-step system GMM estimates of the effect of per capita income growth on bipolar and depression disorders			
	Bipolar	*Depression*	*Bipolar*	*Depression*
Per capita income growth	−0.0520*** (0.0134)	−0.0211** (0.0094)	−0.1373* (0.0754)	−0.0412*** (0.0150)
Public health expenditure	−0.3281*** (0.1211)	−0.1511 (0.1334)	−0.5749 (0.5342)	−0.1161 (0.1414)
Out-of-pocket health expenditure	−0.7459*** (0.2185)	−1.0366*** (0.3201)	−0.0533 (0.4435)	−1.0728* (0.5789)
Population growth	−0.6310*** (0.1591)	−0.4514*** (0.1213)	−1.3349* (0.7099)	−0.4152** (0.1755)
Physician density	−0.6086*** (0.1454)	−0.4613*** (0.1208)	−1.8405* (0.9601)	−1.0304* (0.6023)
Interpersonal violence			9.2692 (6.9945)	0.7701 (0.8307)
Constant	−0.1918 (1.3851)	1.6369 (1.4983)	32.9438 (27.2624)	4.3770** (2.1990)
Observations	145	145	145	145

Notes: Standard errors in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$; Bipolar, depression, health expenditure and interpersonal violence indicators are log-transformed
Source: Authors' computation using data from the GBD and WDI databases

expenditure meets the expected negative sign, it is insignificant (coefficient: −0.008, $p > 0.1$). Also, we find population growth to have a negative significant association with the prevalence of bipolar disorder (coefficient: −0.018, $p < 0.01$) and depression disorder (coefficient: −0.027, $p < 0.01$). In addition, physician density is found to have a negative significant association with the prevalence of bipolar disorder (coefficient: −0.022, $p < 0.01$) and depression disorder (coefficient: −0.021, $p < 0.01$) (Table 4).

Concerning the long-term, we find the results to be similar to that of the short-term. Specifically, regarding per capita income growth, we find it to have a negative significant association with the prevalence of bipolar disorder (coefficient: −0.059, $p < 0.01$) and depression disorder (coefficient: −0.035, $p < 0.1$) (Table 5).

Although health expenditure is insignificant in the prevalence of depression disorder model, we find it to have a negative significant association with the prevalence of bipolar disorder (coefficient: -0.102, $p < 0.05$). Similarly, the relationships between population growth, and the prevalence of bipolar and depression disorders are found to be negative and significant at conventional levels (coefficient: -0.882, $p < 0.01$; and coefficient: -0.910, $p < 0.01$, respectively) (Table 5).

Last but not the least, we find physician density to have negative significant association with the prevalence of bipolar disorder (coefficient: -1.031, $p < 0.01$) and depression disorder (coefficient: -0.704, $p < 0.01$) (Table 5).

3.3.2 Robustness checks results. Using different measures of health expenditure as well as an indicator for violence as control variables, the association between per capita income growth, and bipolar and depression disorders are found to be robust (Tables 6 and 7).

Specifically, controlling for public health expenditure and out-of-pocket health expenditure as well as other variables, we find negative significant relationship between per capita income growth and bipolar (coefficient: -0.001, $p < 0.01$) and depression (coefficient: -0.001, $p < 0.05$) disorders in the short-term. Moreover, after including interpersonal violence as an additional control variable, per capita income growth still exerts its negative significant association with bipolar (coefficient: -0.001, $p < 0.01$) and depression (coefficient: -0.002, $p < 0.01$) disorders in the short-term (Table 6).

Focusing on the long-term estimates, per capita income growth maintains its robustness using the different indicators of health expenditure (bipolar model: coefficient: -0.052, $p < 0.01$; depression model: coefficient: -0.021, $p < 0.05$) as well as controlling for interpersonal violence (bipolar model: coefficient: -0.137, $p < 0.1$; depression model: coefficient: -0.041, $p < 0.01$) (Table 7).

Concerning the control variables, similar to the baseline estimates, we find population growth and physician density to maintain their negative significant association with bipolar and depression disorders in both the short-term and long-term. Nonetheless, while public health expenditure, out-of-pocket health expenditure and interpersonal violence exhibit the expected signs, they are not robust as they are found to be significant in some models and not all the models (Tables 6 and 7).

4. Discussion

In this study, we attempt at providing the first empirical analysis of the effect of per capita income growth on bipolar and depression disorders across 42 African countries. Our findings of negative significant association between per capita income growth, and bipolar and depression disorders in both the short-term and long-term are not farfetched. This is because, as income increases, people will become financially stable, hence, they will not suffer from psychosocial challenges emanating from lack of income (Golberstein, 2015). Moreover, a rise in income would make people more capable of affording quality mental health care as well as other goods that enhance mental health (see Immurana, 2021a). In addition, as a result of higher opportunity cost (earnings lost due to illness), people with higher income may want to adopt preventive measures that will boost their mental health to avoid lost productivity days associated with mental illnesses (see Immurana, 2021b). Based on the above reasons, mental health conditions such as dysthymia and schizophrenia could exhibit similar association with per capita income growth since they share some common features with bipolar and depression disorders.

Our findings are in tandem with a number of past studies. For instance, Golberstein (2015) found an increase in social security income to enhance mental health [depressive symptoms and nervous (psychiatric) challenges] and emotional problems in the USA. In Austria, Pieh *et al.* (2020) reported the highest mental health challenges among people with low income during the COVID-19 period. Relative to individuals with a yearly household income of $70,000 and above, those whose annual household income was less than

$20,000 were found to be associated with a higher likelihood of incident mood disorders in the USA (Sareen *et al.*, 2011). Similarly, cash transfers have been found to be associated with a reduction in depression in India (Powell-Jackson *et al.*, 2016) and Nepal (Tachibana *et al.*, 2019) as well as an improvement in psychological wellbeing in Kenya (Haushofer and Shapiro, 2016). In addition, in Malawi, significant gains in subjective wellbeing have been found to be associated with a short-term rise in household income due to cash transfers (Kilburn *et al.*, 2018). However, some studies have reported conflicting findings. For instance, in Zambia, it was found that perceived stress did not improve as a result of cash transfers (Hjelm *et al.*, 2017), while in Uganda, a poverty alleviation programme was found to have insignificant effect on depression symptoms (Green *et al.*, 2016). The conflicting findings of these studies could be due to differences in the countries used, the study period as well as how income is measured.

Moreover, in the long-term, the apparent higher effect (coefficients) of per capita income growth on bipolar disorder relative to depression disorder could be attributed to the long-term nature of bipolar disorder as compared with depression disorder (see Ellis, 2023).

Notwithstanding, our findings call for deepening economic growth enhancing measures [such as infrastructural development, skills training, technological advancement, attracting more foreign direct investment (FDI) inflows among others] which would result in higher per capita income growth.

As regards the control variables, as rising health expenditure implies higher spending on medical care and other health-enhancing goods and services (Immurana, 2021a), it is not surprising that we find negative significant association between health expenditure indicators and the prevalence of bipolar and depression disorders both in the long-term and short-term. These outcomes are in line with past studies which found health expenditure to enhance health outcomes (Arthur and Oaikhenan, 2017; Nketiah-Amponsah, 2019; Novignon and Lawanson, 2017).

The negative association between population growth and the prevalence of bipolar and depression disorders could be that, rising population growth is being matched with commensurate investments in mental health and general health care (Immurana, 2021a), resulting in better mental health outcomes.

Last but not the least, as the availability of more doctors would enhance access and quality of health care, it is not surprising that, physician density has negative significant association with the prevalence of bipolar and depression disorders on the African continent. These outcomes are in tandem with that of Immurana (2021a) who found physician density to enhance health outcomes in Africa.

Notwithstanding the above, our study is not without limitations. Firstly, the GBD data used faces a challenge of primary data paucity, especially in low- and middle-income countries. In the absence of data, the GBD relies on out-of-sample predictive accuracy during the modelling process. However, major improvements in the estimates will be chalked if more and quality primary data are collected (Vos *et al.*, 2020). Secondly, while our study uses per capita income growth, we acknowledge that it may not necessarily reflect into an improvement in income inequality as well as other inequality indicators. Meanwhile, according to the Wilkinson hypothesis (Wilkinson, 2002), it is not the level of income that affects health but rather, the extent of income inequality. Thirdly, while international aid towards the health sector could affect mental health outcomes, due to data paucity, our study does not include any proxy for international aid in the health sector. Future studies should therefore take into consideration how an improvement in income inequality (as well as other measures of inequality) and international aid in the health sector affect bipolar and depression disorders on the African continent.

5. Conclusion

To the best of our knowledge, this study provides the first empirical evidence of the effect of per capita income growth on the prevalence of bipolar and depression disorders across several African countries. We use data over the period 2002–2019 involving 42 African countries, while employing the dynamic panel system GMM as the empirical estimation technique. Our findings show negative significant association between per capita income growth and the prevalence of bipolar and depression disorders, both in the short-term and long-term. Among others, the study also finds physician density and health expenditure to have negative association with the prevalence of bipolar and depression disorders, both in the short-term and long-term. Thus, to reduce the prevalence of these mental health disorders on the African continent, governments should deepen economic growth enabling measures (including infrastructural development, skills training, technological advancement, attracting more FDI inflows among others) which would result in higher per capita income growth. In doing so, a deliberate attempt should be embarked upon to ensure that the mental health sector receives a befitting share of the benefits associated with growth in per capita income. Moreover, training of more physicians as well as increasing spending in the health sector could greatly help towards improving mental health.

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Declarations: The data used for this study do not contain the identities of any human subjects, and all the appropriate regulations are observed in conducting this study.

Ethics approval and consent to participate: Ethical clearance and consent to participate are not needed since the study employs secondary data.

Availability of data and materials: The data used in arriving at the findings of this study can be accessed freely from the World Bank (https://databank.worldbank.org/reports.aspx?source=World-Development-Indicators#advancedDownloadOptions) and Institute for Health Metrics and Evaluation (https://vizhub.healthdata.org/gbd-results/).

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Since submission of this article, the following authors have updated their affiliations: Kwame Godsway Kisseih is at the Department of Management Studies, Vignan Foundation for Science, Technology and Research, Vadlamudi, India; and Ibrahim Abdullahi is based at the Department of Economics, Memorial University of Newfoundland and Labrador, St. John's, Canada.

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Author affiliations

Mustapha Immurana is based at the Institute of Health Research, University of Health and Allied Sciences, Ho, Ghana.

Kwame Godsway Kisseih is based at the Department of Finance, Christian Health Association of Ghana Secretariat, Accra, Ghana.

Ibrahim Abdullahi is based at the Department of Operations, Safe Haven Insurance Brokers Ltd, Accra, Ghana.

Muniru Azuug is based at the Department of Economics Education, University of Education Winneba, Winneba, Ghana.

Ayisha Mohammed is based at the Department of Languages, Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development, Kumasi, Ghana.

Toby Joseph Mathew Kizhakkekara is based at the PG Department of Economics, EKNM Government College, Elerithattu, India.

Appendix

Table A1 List of countries

Algeria	Cabo Verde	Cote d'Ivoire	Gambia, the	Madagascar	Niger	Tanzania
Angola	Cameroon	Djibouti	Ghana	Mali	Nigeria	Togo
Benin	Central African Republic	Egypt, Arab Rep.	Guinea	Mauritania	Senegal	Tunisia
Botswana	Chad	Equatorial Guinea	Guinea-Bissau	Mauritius	Seychelles	Uganda
Burkina Faso	Congo, Dem. Rep.	Ethiopia	Kenya	Morocco	Sierra Leone	Zambia
Burundi	Congo, Rep.	Gabon	Lesotho	Mozambique	South Africa	Zimbabwe

Source: By authors

Table A2 Summary of studies used in selecting the control variables

Author(s)	*Objective and setting*	*Related control variable(s)*	*Estimation technique*	*Results*
Arthur and Oaikhenan (2017)	To find out how health expenditure affects health outcomes (infant mortality, under-five mortality, life expectancy) in 40 sub-Saharan African countries	Total health expenditure, public health expenditure, private health expenditure	Fixed effects regression	Health expenditure indicators were found to improve health outcomes
Immurana (2021a)	To investigate the effect of FDI on life expectancy and death rate in 43 African countries	Physician density	Fixed effects and random effects regressions	FDI and physician density were found to improve life expectancy and death rate
Nketiah-Amponsah (2019)	To assess the effect of health expenditure on health outcomes (maternal mortality, under-five mortality, life expectancy) in 46 countries in sub-Saharan Africa	Total health expenditure, physician density	Fixed effects and random effects regressions	In general, health expenditure and physician density were found to be associated with improved health outcomes
Novignon and Lawanson (2017)	To find out the effect of health expenditure on child health outcomes in 45 countries in sub-Sharan Africa	Total health expenditure, public health expenditure, private health expenditure	Fixed effects and random effects regressions	While private health expenditure was insignificant, total and public health expenditure were found to enhance child health outcomes
Ziaei and Hammarström (2023)	To find out the relationship between interpersonal violence and mental health symptoms in Sweden	Interpersonal violence	General linear regression	Interpersonal violence was found to have a positive association with mental health symptoms
Arshad *et al.* (2021)	Among others, the study examined the effect of population growth on human development (including health) in Pakistan	Population growth	Autoregressive distributed lag (ARDL) model	The study found a negative association between population growth and human development

Corresponding author

Mustapha Immurana can be contacted at: mustaphaimmurana@gmail.com