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Infant Mortality Rates and GDP Per Capita in Kenya: An Empirical Investigation Based on Fractional Integration.

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Abstract
This paper deals with the analysis of the relationship between the infant mortality rates and the GDP per capita in Kenya using fractional integration and cointegration techniques. The results show that the two series are highly persistent, with the effects of the shocks persisting forever. However, the multivariate work reveals that the two series are fractionally counteracted, showing a long run equilibrium relationship that tends to persist and disappear slowly in the long run. This relationship is important for public policy implying a synergy of development outcomes since it suggests that the current emphasis in Kenya's Vision 2030 on raising per capita income is likely to have positive and long-term effects on the vital health outcome of infant mortality. Our analysis therefore provides additional support for the growth approach to reducing infant mortality. It reinforces the view that growth in per capita income is considered as necessary for sustaining infant mortality improvements although not necessarily sufficient.

Keywords: Infant Mortality Rates; GDP per capita; fractional integration; fractional cointegration.

Introduction
High infant mortality rates have presented a major challenge in developing countries especially in Africa over the last five decades. Kenya has, however, made notable progress especially in the last decade in reducing infant mortality and communicable diseases [1]. Kenya's infant mortality rate has fallen by 7.6 percent per year, the fastest rate of decline among the 20 countries in the region for which recent Demographic and Health Survey data is available [2]. However, health challenges still remain and the poor are particularly vulnerable to health shocks. According to the World Bank, 33.6% of the population in Kenya live on less than the international poverty line of US$ 1.90 per day [3]. In Kenya, like in many other Sub-Saharan African countries, child deaths mostly revolve around child birth and new born deaths contribute to two-thirds of infant mortality. It is interesting to, however, analyse the persistence of infant mortality time series so as to establish whether any changes to infant mortality are transitory or permanent. This will help to establish whether these gains are likely to be sustained and provide an indicator on the degree of policy intervention required. Kenya has also become considerably more prosperous over the last few decades. Kenya's per capita income has risen from US$ 97.62 in 1960 to US$ 1594.83 in 2017 [4]. It would be interesting to determine if this improvement in prosperity has had a long term relationship with infant mortality rates. No study has yet specifically focused on these issues in the Kenyan context, which is reflective of the reality in many lower middle income developing countries. Following the rebasing of its Gross Domestic Product in September 2014, Kenya joined the ranks of lower middle-income countries according to the World Bank classification [5].

In this paper we look at the relationship between the GDP per capita and the infant mortality rate in Kenya for the time period from 1960 to 2014 using techniques based on fractional integration and cointegration, which generalizes the standard stationary / nonstationary (unit root) literature by allowing for a greater degree of flexibility in the dynamic specification of the models. The structure of the paper is as follows: Section 2 contains a short literature review about the infant mortality in Africa and more in particular, in Kenya. Section 3 describes the methodology to be used in the paper; Section 4 is devoted to the empirical work showing the results on the relationship between infant mortality rates and GDP per capita in Kenya. Finally, Section 5 contains some concluding remarks.

Literature Review on Infant Mortality in Kenya and Africa
Mutunga focus on the determinants of infant and child mortality in Kenya. He specifically examines how infant and child mortality is related to the household's environmental and socio-economic

characteristics such as the mother's education, source of drinking water, sanitation facility, type of cooking fuels and access to electricity. He uses a hazard rate framework to analyse the determinants of child mortality [6]. He contends that duration models are easily applicable to child mortality since this class of models accounts for problems such as right-censoring, structural modeling and time varying covariates, which are more difficult for traditional econometric models to handle. A household's environmental and socio-economic characteristics are found to have a significant effect on child mortality. Mutunga contends that policies aimed at achieving the goal of reduced child mortality should be directed to improving the household's environmental or socio-economic status if this goal is to be realized [7].

Mustafa and Odimwegwu examine the relative importance of fundamental biosocial, demographic and economic factors associated with infant mortality in Kenya [8]. They utilize an analytical cross-sectional design through secondary data analysis of the 2003 Kenyan Demographic and Health Survey (KDHS) data set for children. They fit a series of logistic regression models to select the significant factors affecting infant mortality in both urban and rural areas. The magnitude of each selected variable was tested using Wald's test, and hence the factors were rank ordered according to their overall p-value. They find that the significant determinants for infant mortality are breastfeeding, ethnicity and sex of the child while birth order and intervals are significant variables in the rural areas.

Demombynes and Trommlerova analyse what has driven the decline of infant mortality rates in Kenya [2]. Substantial declines in infant and under-5 mortalities have taken place in recent years in many countries in Sub-Saharan Africa. They contend that Kenya's rate of post-neonatal deaths per 1,000 live births fell by more than half over a five-year period, dropping from 47 to 22, as measured using data from the 2003 and 2008-09 Demographic and Health Surveys. Among the possible causes of the decline are various targeted new public health initiatives and improved access to water and sanitation. An Oaxaca-Blinder decomposition using Demographic and Health Survey data shows that the increased ownership of insecticide-treated bednets in endemic malaria zones explains 39 percent of the decline in post-neonatal mortality and 58 percent of the decline in infant mortality. Changes in other observable candidate factors do not explain substantial portions of the decline. The unexplained portion of the decline may be associated with generalized trends such as the overall improvement in living standards that has taken place with economic growth. The widespread ownership of insecticide-treated bednets in areas of Kenya where malaria is rare suggests that better targeting of insecticide-treated bednet provision programs could improve the cost-effectiveness of such programs.

Kimani-Murage et. al examine trends in child infant mortality in Kenya by focusing on urban-rural and intra-urban differentials. They use data from the Kenya Demographic and Health Surveys (KDHS) collected between 1993 and 2008 and the Nairobi Urban Health and Demographic Surveillance System (NUHDSS) collected in two Nairobi slums between 2003 and 2010, to estimate infant mortality rate (IMR), child mortality rate (CMR) and under-five mortality rate (U5MR) [9]. They find that between 1993 and 2008, there was a downward trend in IMR, CMR and U5MR in both rural and urban areas. The decline was more rapid and statistically significant in rural areas but not in urban areas, hence the narrowing of the gap in urban–rural differentials over time. There was also a downward trend in childhood mortality in the slums between 2003 and 2010 from 83 to 57 for IMR, 33 to 24 for CMR, and 113 to 79 for U5MR, although the rates remained higher compared to those for rural and non-slum urban areas in Kenya.

Some studies have been carried out in the African context on the links between economic growth and child health in Sub-Saharan Africa, for example, by O'Hare et. al but none using the more general techniques of fractional integration. Hanmer et. Alm, in a broad developing country study consider whether development is best achieved by focusing on growth, or whether specific attention needs to be paid to directly improving human welfare [10, 11]. In contrast to the Human Development Report approach of the United Nations Development Programme, the World Bank has stressed the growth approach. A vital implication of the growth approach is that health expenditure is extremely ineffective in reducing infant or child mortality, which is mainly explained by a country's income per capita. Their paper tests the robustness of the determinants of infant and child mortality arguing that, while income per capita is a robust determinant of infant and child mortality, so are indicators of health, education and gender inequality. Some health spending, such as immunisation, is therefore shown to be a cost effective way of saving lives. Their results are consistent with the view that much health spending in developing countries may be poorly targeted or otherwise ineffective, but do not support the position that public health strategies should not be given too great a role in pursuing improvements in human welfare. Another broad study was carried out by O'Hare et. al to incorporate developing countries outside Africa [12].

They conduct a systematic literature search of studies that examined the relationship between income and child mortality and meta-analysed their findings. They find that income is an important determinant of child survival. Asiedu et. al. examine the impact of income per capita on broader health outcomes in Africa including adult life expectancy and mortality rates for children using an overlapping generations model [13]. However, fractional integration techniques were not used in any of these studies. No study in the Kenyan context or African context has yet done a univariate time series analysis of infant mortality trends using fractional integration techniques and neither has any study specifically examined the long run relationship between infant mortality and GDP per capita using fractional cointegration techniques. These are therefore, the two main contributions of the work.

Methodology

We present in this section the modelling approach. For the univariate analysis we use techniques based on the concept of fractional integration that means that we take potential fractional degrees of differentiation on the series to render it stationary I (0). By I (0) we mean a process that is covariance stationary and where the infinite sum of the autocovariances is finite, that is, it may be a white noise, but also a (weakly) autocorrelated process of the ARMA form. Having said this, we say that a process {xt, t= 0, ±1, …} is integrated of order d, and denoted by I(d) if it can be represented as

$$(1-L)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{1}$$

with $x_t = 0$, $t \le 0$, L is the lag operator (i.e., $Lx_t = x_{t-1}$), and where u_t is $I(0)$. Fractional integration takes place when d is a fractional value. Note that the polynomial on the left-hand-side of equation (1) can be expanded, for all real d, as

$$(1-L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots, \tag{2}$$

implying that x_t in (1) can be written as:

$$x_t = d\, x_{t-1} - \frac{d(d-1)}{2} x_{t-2} + \ldots + u_t. \tag{3}$$

Thus, if d is a fractional value, the actual value of x (x_t) depends on all its past history, and the higher the d is, the higher the level of dependence is between the observations. Processes with d > 0 in (1) display the property of "long memory" or "long range dependence", because of the strong association between observations that are far distant in time. This type of processes provides a much richer degree of flexibility in the dynamic specification of the series than the standard models based on integer degrees of differentiation (stationarity I (0) and nonstationarity I (1)), widely employed in the time series literature. Moreover, they have been widely employed in recent years in modelling time series in many different disciplines including economics etc [14-28].

In the empirical application carried out in the following section we employ first two parametric approaches based on the Whittle estimate of the differencing parameter d along with several semi-parametric methods [29-34].

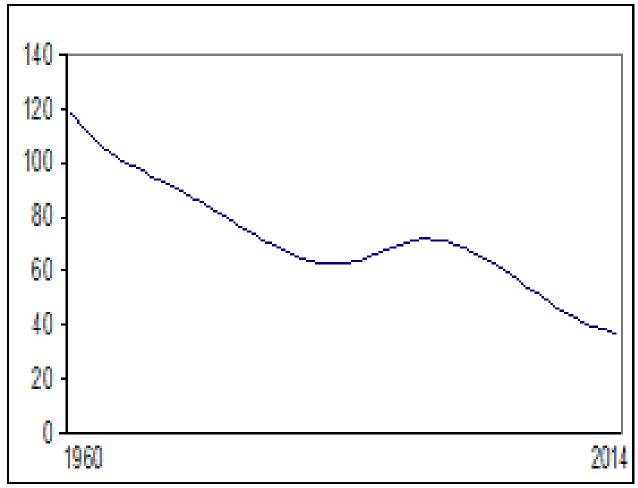
In the multivariate case, we use techniques based on fractional cointegration. In a broad sense, given two real numbers d, b, the components of the vector zt are said to be cointegrated of order d, b, and denoted zt ~ CI(d, b) if:

i. all the components of z_t are I(d),
ii. there exists a vector α ≠ 0 such that st = α'z_t ~ I(γ) = I (d – b), b > 0.

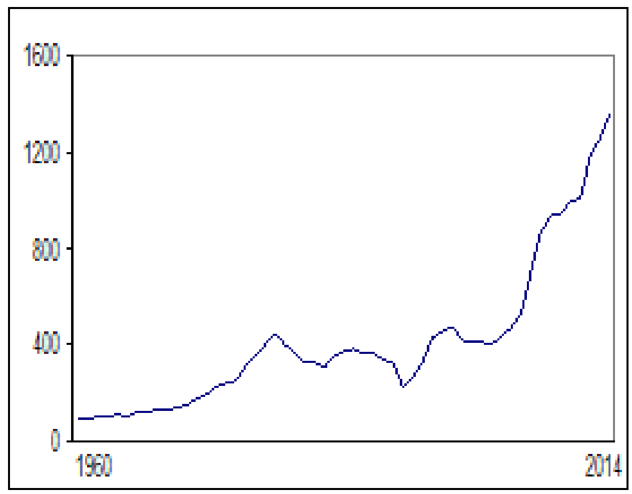
Here, α and s_t are called the cointegrating vector and error respectively. In the paper we conduct the following strategy: We first estimate individually the orders of integration of the two series using the semiparametric approach of Robinson [31]. Next we test the homogeneity of the orders of integration in the bivariate systems (i.e., H_o: $d_x = d_y$), where dx and dy are now the orders of integration of the two individual series, by using an adaptation of Robinson and Yajima statistic to log-periodogram estimation, in addition to another method [31, 35, 36]. The functional form of the test statistics can be found in Gil-Alana and Hualde [37]. In the final step, we perform the Hausman test for no cointegration of Marinucci and Robinson comparing the estimate d_x of d_x with the more efficient bivariate one of Robinson, which uses the information that $d_x = d_y = d^*$ [31, 38].

Data and Results

The data used in the paper are the following: they are annual data obtained from World Bank Kenya Country Meta database for the period 1960 to 2014. The GDP per capita data are in current US dollars. The infant mortality rate is expressed per 1000 live births.



IMR



GDP per capita

Figure 1 displays the time series plots along with their logged and logistic transformations. We observe that the IMR data have been reducing across the sample period with a sudden increase around the mid 80s until the late 90s, and then decreasing again till the end of the sample. For the GDP per capita, the values increased at the beginning of the sample, stabilizing during the crisis, and then starting to increase again since the mid/late 90s. In general, the two series have an appearance of nonstationary, with a very persistent pattern.

Across Table 1 we display the estimated values of the fractional differencing parameter, d, in the model given by

$$y_t = \beta_0 + \beta_1 t + x_t, \quad t = 1, 2, \ldots \tag{4}$$

$$(1-L)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{5}$$

where y_t refer to each of the two observed time series (IMR and GDP per capita); β_0 and β_1 are the coefficients corresponding respectively to the intercept and a linear time trend, and xt is supposed to be I(d) adopting different forms such as white noise and autocorrelated throughout the model of Bloomfield, which is a non-parametric approach of modeling I (0) errors and that produces autocorrelations decaying exponentially as in the autoregressive case [39]. Table 1(Panel A) focuses on the original data; Panel B on the logged transformed values, and Panel C displays the results based on the logistic transformation of the IMR data.2

Table 1: Estimates of d and 95% intervals

Panel A			
i) GDP per capita			
	No regressors	An intercept	A linear time trend
White noise	1.39 (1.22, 1.65)	1.39 (1.21, 1.68)	1.40 (1.22, 1.68)
Autocorrelated	1.20 (0.92, 1.60)	1.18 (0.87, 1.57)	1.19 (0.87, 1.58)
ii) Infant Mortality Rate			
	No regressors	An intercept	A linear time trend
White noise	0.90 (0.72, 1.15)	2.24 (2.00, 2.58)	2.23 (2.10, 2.39)
Autocorrelated	0.73 (0.37, 1.20)	1.74 (1.43, 2.22)	2.95 (2.35, 3.97)
Panel B			
i) GDP per capita (in logs)			
	No regressors	An intercept	A linear time trend
White noise	0.95 (0.78, 1.18)	1.24 (1.00, 1.56)	1.23 (1.00, 1.56)
Autocorrelated	0.85 (0.51, 1.27)	0.81 (0.38, 1.42)	0.87 (0.53, 1.41)
ii) Infant Mortality Rate (in logs)			
	No regressors	An intercept	A linear time trend
White noise	0.92 (0.75, 1.16)	2.06 (1.91, 2.28)	2.03 (1.91, 2.17)
Autocorrelated	0.77 (0.42, 1.23)	2.10 (1.74, 1.23)	2.21 (2.74, 3.92)
Panel C			
Infant Mortality Rate (logistic)			
	No regressors	An intercept	A linear time trend
White noise	0.92 (0.76, 1.16)	2.02 (1.88, 2.21)	2.00 (1.88, 2.14)
Autocorrelated	0.77 (0.42, 1.21)	2.09 (1.74, 2.64)	2.73 (2.21, 3.98)

Starting with the results for the original data we observe that the estimated value of d is significantly higher than 1 for GPD per capita under white noise disturbances though the unit root null (i.e. d = 1) cannot be rejected with autocorrelated errors. This result seems to be robust for the three different cases of no deterministic terms, an intercept and an intercept with a linear time trend. However, for the IMR series, the results substantially change depending or not on the incorporation of deterministic terms. If these terms are included, the estimated value of d is much higher than 1 (in fact, even higher than 2 with a linear time trend) though the unit root null cannot be rejected in the context of no regressors. Very similar results are presented in Panel B for the logged transformed data. Thus, the unit root null cannot be rejected for the GPD per capita series; the same happens for the IMR data with no deterministic terms, but this hypothesis is decisively rejected in favour of much higher degrees of integration under deterministic terms. The same holds for the logistic IMR transformation as shown in Panel C.

Table 2: Semiparametric estimates of d in the original data

Panel A (original data)							
	6	7	8	9	10	11	12
CAP	1.088	1.161	1.204	1-207	1.152	1.207	1.281
MR	2.500	2.500	2.362	2.286	2.229	2.193	2.191
Panel B (logged and logistic data)							
	6	7	8	9	10	11	12
LCAP	0.761	0.816	0.926	0.969	0.948	1.011	1.084
LMR	2.500	2.500	2.300	2.108	2.055	2.020	2.007
Logistic	2.500	2.500	2.349	2.181	2.105	2.053	2.019

Next we report the results about the estimated values of d using a semiparametric method for a selected number of bandwidth numbers (from m = 6 to 12).3 The results for the original data are displayed in Table 2 (Panel A), while Panel B refers to the logarithmic and logistic transformation [31]. Again the same type of conclusions can be drawn from these tables. The fractional differencing parameters is close to 1 for the GPD per capita series but it is close to 2 for the IMR data.

Given the disparity in the degree of integration between the two series, the possibility of non-linear structures is also taken into account. In particular, we use here a non-linear approach proposed by Cuestas and Gil-Alana (2016), and based on the Chebyshev polynomials in time,

$$y_t = \sum_{i=0}^{m} \theta_i P_{iT}(t) + x_t, \qquad (1 - L)^d x_t = u_t, \qquad (6)$$

assuming again that u_t is a white noise process and autocorrelated, throughout the model of Bloomfield (1973). The Chebyshev polynomials $P_{i,T}(t)$ in (6) are defined as:

$$P_{0,T}(t) = 1,$$
$$P_{i,T}(t) = \sqrt{2}\cos\left(i\pi(t-0.5)/T\right), \qquad t = 1, 2, \ldots, T; \quad i = 1, 2, \ldots \qquad (7)$$

(see Hamming and Smyth for a detailed description of these polynomials) 40 [41, 42].

Bierens uses them in the context of unit root testing. According to Bierens and Tomasevic and Stanivuk, it is possible to approximate highly non-linear trends with rather low degree polynomials. If m = 0 in (6), the model contains an intercept, if $m = 1$ it also includes a linear trend, and if $m > 1$ it becomes non-linear - the higher m is the less linear the approximated deterministic component becomes [43, 44].

Table 3: Estimates of d and nonlinear Chebyshev coefficients

Panel A (original data)					
i) GDP per capita					
	d	θ_1	θ_2	θ_3	θ_4
White noise	1.32 (1.11, 1.61)	293.99 (0.60)	-72.11 (-0.23)	36.71 (0.33)	-102.25 (-1.59)
Bloomfield	0.88 (0.24, 1.39)	505.06 (3.70)	-253.94 (-3.26)	94.83 (2.12)	-132.51 (-4.23)
ii) Infant Mortality Rate					
	d	θ_1	θ_2	θ_3	θ_4
White noise	2.19 (1.89, 2.58)	141.28 (2.53)	-18.88 (-0.49)	-0.12 (-0.01)	4.59 (1.24)
Bloomfield	1.45 (1.07, 1.68)	94.90 (8.11)	8.50 (1.71)	3.24 (1.73)	6.36 (4.69)
Panel B (logged data)					
i) GDP per capita					
	D	θ_1	θ_2	θ_3	θ_4

White noise	1.05 (0.67, 1.48)	5.91 (12.39)	-0.62 (-2.19)	-0.03 (-2.28)	-0.28 (-3.22)
Bloomfield	0.92 (-0.86, 1.68)	5.77 (434.94)	-0.62 (-40.85)	-0.03 (-2.27)	-0.28 (-16.85)
ii) Infant Mortality Rate					
	d	θ_1	θ_2	θ_3	θ_4
White noise	1.94 (1.74, 2.20)	4.85 (11.37)	-0.15 (-0.54)	0.03 (0.50)	0.07 (2.19)
Bloomfield	1.53 (1.36, 1.64)	4.56 (12.71)	1.61 (0.04)	-1.72 (-0.03)	0.08 (2.18)
Panel C (logistic)					
Infant Mortality Rate (logistic)					
White noise	1.88 (1.71, 2.13)	1.71 (21.76)	-0.03 (-0.63)	0.08 (0.62)	0.01 (2.35)
Bloomfield	1.46 (1.41, 1.68)	1.64 (31.15)	1.67 (0.44)	1.82 (1.06)	0.02 (3.74)

In bold, in columns 3 – 6, significant coefficients at the 5% level.

Table 3 displays the estimated values of d along with the Chebyshev polynomial coefficients for the two cases of uncorrelated and Bloomfield-type errors, first for the original data (Panel A), for the logged transformed data (Panel B) and for the logistic IMR transformation (in Panel C). We observe several statistically significant coefficients, especially for the IMR series, and the fractional differencing parameter is now substantially smaller for the IMR series. In fact, the unit root null is still rejected, however, the confidence intervals in the two series (GDP per capita and IMR) overlap each other, suggesting that they can be statistically similar. For example, and focusing on the original data, the estimated value of d for the GPP per capita under autocorrelated errors is equal to 0.88, and the confidence interval (0.24, 1.39) is wide enough to include the unit root null. For the IMR data and also using autocorrelated errors, d is equal to 1.45 and the interval is now between 1.07 and 1.68. Very similar results are obtained with the logged and logistic transformations (Panels B and C in Table 3).

This is the basis that allows us to proceed with the multivariate work. A necessary condition in a bivariate cointegration approach is that the two individual series must display the same degree of integration, and though in the three cases of the original data, the log and logistic transformations, the values of d differ, performing the Robinson and Yajima approach based on log-periodogram-type of estimators we cannot reject the homogeneity condition in the degree of integration in any of the three cases [31, 35].

Table 4: Fractional cointegration results based on linear regression models

Panel A (original data)			
$IMR_t = \alpha + \beta\, CAP_t + x_t; \quad (1 - l)d\, x_t = u_t$			
	d (95% band)	α (t-value)	β (t-value)
White noise	2.24 (2.01, 2.59)	120.888 (308.57)	-0.00051 (-0.34)
AR (1)	0.21 (0.10, 0.40)	95.895 (18.78)	-0.0513 (-6.12)
Bloomfield	1.74 (1.37, 2.26)	120.816 (253.31)	-0.000012 (-0.007)
Panel B (logged data)			
$Log(IMR_t) = \alpha + \beta\, Log(CAP_t) + xt; \quad (1 - l)d\, x_t = u_t$			
	d (95% band)	α (t-value)	β (t-value)
White noise	2.06 (1.90, 2.28)	4.7968 (121.01)	-0.00028 (-0.03)
AR (1)	0.14 (-0.09, 0.29)	6.4675 (20.45)	-0.3861 (-7.12)
Bloomfield	2.09 (1.74, 2.65)	4.7965 (122.78)	-0.00019 (-0.02)

Panel C (logistic)			
Logistic (IMR_t) = α + β Log (CAP_t) + x_t; $(1 – l)d\ x_t = u_t$			
	d (95% band)	α (t-value)	β (t-value)
White noise	2.06 (1.92, 2.25)	5.4858 (137.78)	-0.00027 (-0.03)
AR (1)	0.14 (-0.09, 0.31)	7.1705 (22.54)	-0.3891 (-7.12)
Bloomfield	2.09 (1.73, 2.63)	5.4855 (139.18)	-0.00019 (-0.02)

In bold, in columns 3 – 4, significant coefficients at the 5% level.

In Table 4 we display the results of the regressions of IMR on GDP per capita on the original data (Panel A), logged data and using the logistic transformation for IMR ((Panel C). In fact, this is an extension of the Engle and Granger's approach to the fractional case [13, 45, 46]. As expected the β-coefficient is negative in all cases but only statistically significant in the context of AR (1) disturbances, and more importantly, the estimated value of d is substantially smaller than 1. In fact, for the original data, the value is about 0.21 and the two hypotheses of integer degrees of differentiation (d = 0, i.e., standard cointegration, and d = 1, i.e., no cointegration) are decisively rejected in favour of a fractional value. For the logged and logistic data, the estimated value of d is 0.14 and in this case the I (0) hypothesis cannot be rejected at conventional significance levels.

Table 5: Hausman test of no cointegration (Marinucci and Robinson, 2001)

Series	d1 (IMR)	d_2 (GPD)	d*	H (d1 = d*)	H (d2 = d*)
Original	1.456	0.883	0.211	86.801	25.288
Logged	1.531	1.058	0.144	107.731	46.872
Logistic	1.462	1.058	0.141	97.722	47.089

In bold, rejection of the null of no cointegration at the 5% level.

As a final step, we conduct the Marinucci and Robinson's method, comparing the estimates of the individual series obtained above with the more efficient bivariate one of Robinson, which uses the information that the series share the same degree of integration [31, 38]. The results for a bandwidth number m = (T)0.5 are reported in Table 5 and we observe strong evidence against the null of no cointegration and in favour of fractional cointegration.

Concluding comments

The GDP series shows a high degree of persistence with levels of d being greater than one under different formulations of the error term and hence indicating the persistence of shocks in per capita income. Positive changes in per capita income in Kenya are therefore likely to be sustained over time if critical growth policies under Kenya's Vision 2030 are maintained. For the infant mortality series, the results substantially change depending or not on the incorporation of deterministic terms. The unit root hypothesis for the infant mortality series cannot be rejected in the absence of deterministic terms but this hypothesis is decisively rejected in favour of much higher degrees of integration under deterministic terms. Using semiparametric and non-linear approaches the persistence of the infant mortality series is, however, confirmed. This suggests that under most analysed formulations, positive changes to infant mortality in Kenya in recent years are likely to be sustained in the future. In terms of the relationship between the per capita income and infant mortality series, we observe strong evidence in favour of fractional cointegration suggesting that a long run relationship exists between income per capita and infant mortality in Kenya though it takes a long period of time to converge. This is important for public policy since it suggests that the current emphasis on raising income per capita is likely to have positive effects on the critical health outcome of infant mortality in Kenya. Economic policy in Kenya is currently focused on the "big four" agenda which prioritizes food security, manufacturing, affordable universal health care and affordable housing. The focus on healthcare further accentuates the nexus between health policy and economic prosperity [47].

Our findings provide an empirical basis for reinforcing the per capita income-infant mortality nexus, which is an important aspect of current public policy in Kenya. The findings also imply vital synergies in public policy outcomes in the Kenyan context. This is in line with the growth approach to reducing infant mortality which contends that increasing a country's income per capita is a vital pillar of improving important health outcomes. Growth in per capita income in Kenya is considered as being necessary for sustaining infant mortality improvements although not necessarily sufficient. Additional work is required to identify the most effective social policy interventions. Lower infant mortality in turn has positive effects on sustaining the benefits from Kenya's demographic dividends, which is dependent on the survival of its young population. Other lower middle income countries in Africa with similar economic characteristics to Kenya can also be encouraged to continue emphasizing polices aimed at raising GDP per capita as this is likely to contribute to better health outcomes.

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