Department of Economics and Finance

Working Paper No. 2306

Economics and Finance Working Paper Series

Guglielmo Maria Caporale, Juan Infante, Marta del Rio, and Luis A. Gil-Alana

Measuring Persistence of The World Population: A Fractional Integration Approach

February 2023

http://www.brunel.ac.uk/economics

1. Introduction

The world population has increased sharply over the history of the planet. 12,000 years ago, it was only 4 million, which would now be the size of a city. Currently, it is 1860 times larger than at that time (see https://ourworldindata.org/world-population-growth). Its most significant growth has occurred in modern times: its size was still under 1 billion at the beginning of the 19th century (Kremer, 1993); it then increased sevenfold, the current population representing 6.5% of the total number of individuals born during the entire history of mankind, which was estimated to have been 108 billion (Haub, 1995). Growth was particularly rapid between 1950 and 1987, when the world population increased from 2.5 to 5 billion, the highest growth rate (2.1%) being recorded in 1962; since then, growth has decelerated, though it remains fast (Roser et al., 2013).

It should be noted that growth is driven by the difference between births and deaths. Most recently, the increase in deaths has not been matched by a similar one in births, which implies that the world population growth may halt in the near future. The 'demographic transition' model (Kirk, 1996) explains how growth occurs by identifying five different stages, namely: (i) Stage 1: mortality and birth rates are both high; (ii) Stage and sheds light on whether or not the series is mean-reverting (and thus whether the effects

Figure 1 displays the evolution over time of the first differenced series. It can be

$$H_o: \ d \quad d_o, \qquad (4)$$

(for the empirical properties of this test, see Gil-Alana and Robinson, 1997; Gil-Alana and Moreno, 2012; Abbritti et al., 2016; etc.).

Three model specifications are considered, namely without deterministic terms, with an intercept only, and with an intercept as well as a linear time trend. Table 1 displays the estimates of d alongside their 95% confidence intervals, for both the original and the log-transformed data, under the assumption of white noise residuals, whilst Table 2 presents the results when allowing for autocorrelation in the error term u_t,; in both cases the coefficients in bold are those from the specification selected on the basis of the statistical significance of the regressors. Note that for the case of autocorrelated residuals we use the exponential spectral model of Bloomfield (1973), which is well suited to the framework proposed by Robinson (1994) and applied in this study. This specification approximates AR structures in a non-parametric way, and results in rapidly decaying autocorrelation coefficients (see, e.g., Gil-Alana, 2004).

TABLES 1 - 3 ABOUT HERE

Concerning the results with white noise residuals (Table 1), it can be seen that the time trend is not statistically significant, and the estimated value of d is greater than 1 for both the original data (1.46) and

TABLES 4 AND 5 ABOUT HERE

Given the long time span, it is possible that breaks have occurred. Therefore we carry out the break tests. These results are reported in Table 4. Three breaks are detected in the case of the original data (1915, 1948 and 1981) and five in the case of the logged ones (1832, 1880, 1915, 1948 and 1981). The same number of breaks (and break dates) is found in both cases for the growth rates, which are calculated as the first differences of the logged series. However, splitting the sample accordingly would yield very short subsamples with unreliable estimates. Therefore, we carry out the tests again allowing for a single break only. This appears to have occurred in 1948 in the case of the original data, and in 1946 for the logged series and the growth rate (Table 5).

TABLES 6 - 8 ABOUT HERE

Tables 6, 7 and 8 report the estimated values of d corresponding to the two subsamples based on the detected breaks for each of the three series (original data, log-transformed ones, growth rates), again for the three specifications without deterministic terms, with an intercept only, and an intercept as well as a linear time trend. It is noteworthy that in the case of the original series (Table 6) there is a substantial reduction in the degree of integration after the break, the estimated value of d decreasing from above 2 (or even 3) before the break to 1 or around 1 after it. Similar evidence is obtained when using the logged values (Table 7), namely the degree of integration falls sharply after the break; in addition, there is now a significant positive trend in the second subsample. Finally, in the case of the growth rates (Table 8) there is a decrease in the degree of integration from the first to the second subsample (from 2.66 to 0.52 with white noise errors and from 1.05 to 0.58 with autocorrelated ones), but the time trend is now negative and significant in the second subsample regardless of the specification for the error term.

4. Conclusions

This paper uses fractional integration methods to measure the degree of persistence in historical annual data on the world population over the period 1800-2016. The analysis is carried out for the original series, and also for its log transformation and its growth rate. The results indicate that the series considered are highly persistent; in particular, the estimated values of the fractional diffencing parameter are above 1, which implies that shocks have permanent effects.

It should be noted that these findings could be biased in the presence of structural breaks which have been overlooked. Therefore we also carry out endogenous break tests which suggest that the main break in the data occurred shortly after the Second World War. The evidence based on the corresponding sub-sample estimation indicates a sharp fall in the degree of dependence between the observations in the second sub-sample. However, in the case of the original data and their log transformation they are still above 1, which implies explosive behaviour and permanent effects of exogenous shocks; in addition, there is a statistically significant positive time trend. By contrast, the growth rate of the world population, though not covariance stationary, is mean-reverting, and thus shocks to this series will only have transitory effects; moreover, there is a negative time trend. This represents important information for policy makers concerned with demographic trends, since it suggests that there are already some factors at work (such as a fall in fertility) slowing down growth in the world population; this should be taken into account when designing policies aimed at containing population growth owing to the limited resources of the planet.

References

Abbritti, M., Gil-Alana, L. A., Lovcha, Y., and Moreno, A. (2016). Term structure persistence. *Journal of Financial Econometrics*, *14*(2), 331-352.

Bai, J., and Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of applied econometrics*, *18*(1), 1-22.

Bhargava, A. (1986). On the theory of testing for unit roots in observed time series. *The Review of Economic Studies*, *53*(3), 369-384.

Birdsall, N. (1988). Economic approaches to population growth. *Handbook of development economics*Qq0.000008871 0 595.32 841.92 reW*nBT/F6 12 Tf1 0 0 1 226.73 635.7 s2 reW*n

Figure 1: Time series plot

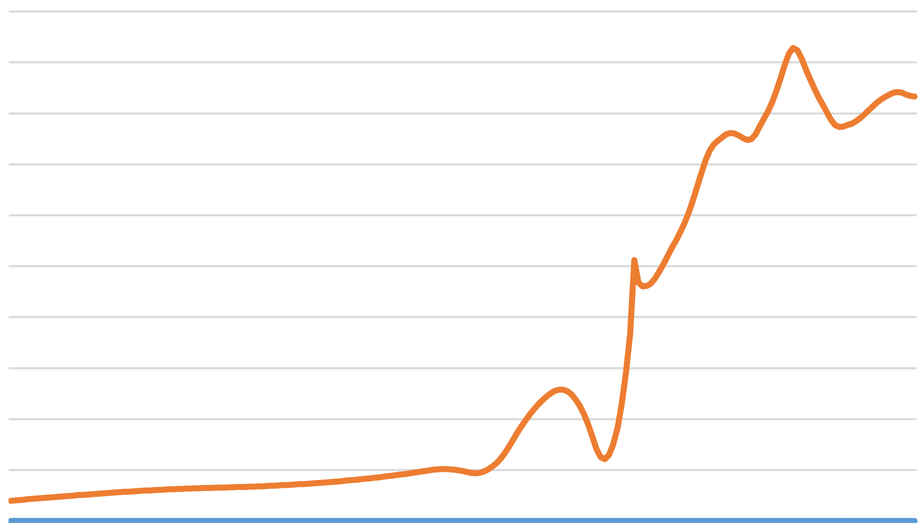

Table 1: Estimates of the differencing parameter, d - White noise errors

Series	No terms	With a constant	With a constant and a linear time trend
Original	1.44 (1.34, 1.57)	**1.46 (1.36, 1.59)**	1.46 (1.36, 1.59)
Log-transformed	0.98 (0.90, 1.10)	**1.78 (1.66, 1.92)**	1.78 (1.66, 1.92)

The values in bold are those from the model selected on the basis of the statistical significance of the regressors. The values in parenthesis are the confidence bands at the 95% level.

Table 2: Estimates of the differencing parameter, d - Autocorrelated errors

Series	No terms	With a constant	With a constant and a linear time trend
Original	1.38 (1.18, 1.72)	**1.41 (1.19, 1.75)**	1.41 (1.20, 1.75)
Log-transformed	0.95 (0.81, 1.15)	**1.71 (1.30, 2.20)**	1.71 (1.30, 2.20)

The values in bold are those from the model selected on the basis of the statistical significance of the regressors. The values in parenthesis are the confidence bands at the 95% level.

Table 3: Estimates of the differencing parameter, d, for the growth rate series

Series	No terms	With a constant	With a constant and a linear time trend

Table 7a: Sub-sample estimates of the differencing parameter, d - Logged data

i) White noise errors			
Series	No terms	With a constant	With a constant and a linear time trend
1800 - 1948	0.99 (0.89, 1.14)	3.52 (3.07, 4.09)	**3.66 (3.15, 4.15)**
1949 - 2016	0.98 (0.83, 1.19)	1.46 (1.24, 1.76)	**1.39 (1.20, 1.65)**
ii) Autocorrelated errors			
Series	No terms		

Table 8a: Estimates of the differencing parameter, d - Growth rates

i)