University of Connecticut

Department of Economics Working Paper Series

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Working Paper 2016-17
September 2016

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The Relationship between Population Growth and Standard-of-Living Growth Over 1870-2013: Evidence from a Bootstrapped Panel Granger Causality Test*

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Abstract: This paper examines the linkages between population growth and standard-of-living growth in 21 countries over the period of 1870-2013. We apply the bootstrap panel causality test proposed by Kónya (2006), which accounts for both dependency and heterogeneity across countries. We find one-way Granger causality running from population growth to standard-of-living growth for Finland, France, Portugal, and Sweden, one-way Granger causality running from standard-of-living growth to population growth for Canada, Germany, Japan, Norway and Switzerland, two-way causality for Austria and Italy, and no causal relationship for Belgium, Brazil, Denmark, Netherlands, New Zealand, Spain, Sri Lanka, the UK, the USA, and Uruguay. Dividing the sample into two subsamples due to a structural break yields different results over the two periods of 1871-1951 and 1952-2013. Our empirical results suggest important policy implications for these 21 countries as the directions of causality differ across countries and time period.

Keywords: Population Growth; Standard-of-Living Growth; Dependency and Heterogeneity; Bootstrap Panel Causality Test

JEL Classification: C32, C33, O40, Q56

* We would like to thank two anonymous referees for many helpful comments. Any remaining errors, however, are solely ours.

1. Introduction

The causal linkages between population growth and standard-of-living growth remain an important issue, not only for demographers and economists, but also for policy makers. The standard of living equals the ratio of real GDP to population, giving real GDP per capita. Thus, the standard of living increases (decreases) when economic growth (i.e., the growth rate of real GDP) exceeds (falls below) the population growth rate.

Researchers typically attribute the development of the linkages between the standard of living and population growth to Malthus (1798). Malthusian theory includes several assumptions. First, a fixed supply of arable land and the absence of improvements in production technology ensure diminishing returns to population. Second, a higher standard of living leads to faster population growth. Third, faster population growth, leads to a declining standard of living. Finally, the economy reaches a steady state either through "preventative" (intentional lowering of fertility) or "positive" (malnutrition, illness, and famine) checks.

Galor and Weil (2000) develop and analyze a model of economic growth that introduces technical change and demographic transition between three different, but related, models -- Malthusian, Post-Malthusian, and Modern Growth models. The Malthusian model incorporates the assumptions outlined above. The Post-Malthusian model relies on technical change to break the link between faster population growth and a lower standard of living. Finally, the Modern Growth model adds demographic transition to the Post-Malthusian model to break the link between a higher standard of living and faster population growth.

This paper considers the causal link between population growth and standard-of-living growth, using long historical time-series data over 1870-2013. Recent experience in economic dynamics shows that turbulence in one region may easily transmit to other regions through international trade and economic and financial integration, implying the importance of considering cross-section dependence in empirical analysis. Previous studies that examine the correlation between population growth and economic growth do not examine the possible two-way inter-relationship. Even though strong dependence exists between countries, each country experiences its own dynamics in the process of development. The panel causality method that this paper uses controls for dependency across countries as well as country-specific characteristics. When examining the causal linkages between the variables of interest, we separately test for both cross-section dependence and cross-region heterogeneity, using recently developed, statistically powerful tests instead of arbitrarily assuming the existence of these features in the panel data set. We contribute to the existing literature by addressing these two concerns jointly, which will bias estimation in panel data structure, if not accounted for.

Afzal (2009) argues that cross-national evidence on the relationship between population growth and economic growth is inconsistent because the underlying parameters and assumptions vary across countries. We apply the bootstrap panel causality test proposed by Kónya (2006) to discover the dynamic and causal relationships between population growth and economic growth for 21 countries over the period 1870-2013, testing for both dependency and heterogeneity across countries. The panel data Granger causality approach, instead of time-series methods, includes information not only from a time-series dimension, but also from a cross-sectional dimension. As a result, we control for country-specific effects. Based on this advantage, non-stationary panel tests (unit root, cointegration, and causality) introduce a more powerful econometric methodology.

To the best of our knowledge, we are the first to examine the relationship between population and standard-of-living growth for 21 countries, using such a long time data series and a bootstrap panel Granger causality test. We adopt the econometric methodology of Kónya (2006) that permits contemporaneous correlation across regions. We use this more meaningful and effective methodology, because the cross-country interaction between economic sectors usually exists, as compared to cross-country analysis or time-series analysis on a country-by-country basis. This study fills the void in current literature regarding population and standard-of-living growth.

This paper is organized as follows. Section 2 reviews some previous literature. Section 3 presents the data and hypotheses. Section 4 describes the bootstrap panel Granger causality test proposed by Kónya (2006). Section 5 presents our empirical results. Section 6 concludes.

2 Literature on the Population and Economic Growth Nexus

The existing literature on the relationship between population and economic growth is not only huge, but also diverse, trying to validate different schools of thought. According to Luigi et al. (2010), we can group these schools into three main categories, indicative of either a negative, positive, or neutral relationship. As noted earlier, Malthus (1798) argued that population growth decreases per capita output, because output growth cannot keep pace with that of population growth. Malthus (1798) also argued that higher per capita output increases population growth. In other words and according to Malthus (1798), the causal relationship between population growth and economic growth can exhibit a bi-directional relationship, where the sign of the relationship contingent on which variable serves as the causal variable.

Building on Malthus' (1798) first proposition that population growth negatively affects economic growth, much theoretical literature followed. In the neoclassical growth model, Solow (1956) treated population as an exogenous variable and assumed that population growth followed an arithmetic pattern instead of a geometric one. Based on this, Solow (1956) built a model using an exogenous population growth rate, where it produced two distinct effects on output growth. On the one hand, an increase in the population growth rate will increase the amount of labor and, thus, both the absolute level of output and the steady-state output growth rate. On the other hand, it will also reduce the physical capital stock per worker; therefore, decreasing productivity and the steady state output per worker. That is, higher population growth *per se* is detrimental to economic development, or the standard of living.

Mason (1988) demonstrated both theoretically and empirically that population growth may reduce the propensity to save and lower potential investment. This leads to a further decrease in physical capital per worker and, thus, in the per capita steady-state output. Though Easterlin (1967) argues that Mason's findings relate to the limited availability of physical capital, which does not affect the exogenously determined population growth, he agreed that population growth constrains economic growth.

In general, this school of thought implies that higher population growth, which is exogenously determined, will limit economic growth and, therefore, it supports population control policies, especially in developing countries. Decreasing population growth proves a necessary and important step to improve living conditions, because it will increase the available per capita resources (see Easterlin, 1967). According to Toney et al. (1981), the Malthusian and neo-Malthusian position receives a wide consensus with few exceptions.[1]

Other researchers in the second school of thought (Modern Growth and Post-Malthusian models) challenge Malthusian theories from an economic point of view (Kuznets et al., 1960). These authors highlight the positive effect of population growth on economic growth. They consider three major economic activities (production, consumption, and saving), which, in turn, contribute to economic growth. Kuznets (1976) provided more empirical evidence on the beneficial effects of population growth as a counter to Malthusian theories. Kremer (1993) empirically confirmed that larger population growth associated with higher population growth and faster technology improvement, which is a consequence of population growth, and leads to an increase of labor productivity, per capita income, and living standards. These researchers shift the focus from natural and reproducible physical capital to knowledge and innovation. Therefore, production was freed from the diminishing

[1] The literature typically focuses on the relationship between population growth and economic growth, rather than standard of living growth. An older, but comprehensive literature review can be found in Cassen (1976).

returns that characterized the previous economic analysis. According to Espenshade (1978), this view calls for policy advice that supports increased fertility and immigration in countries with declining or stationary population.

More recently, another group of researchers in the final school of thought argue that the increase in population does not affect economic growth, but the former variable does not hamper the latter (Simon, 1987). The issue relates to the employment, development, and distribution of the increased population (Kuznets, 1955; Todaro and Smith, 2006) for high-population countries.

Recall that Malthus (1798) also suggested that that higher per capita output increases population growth, support for which appears in studies such as Dasgupta (2000), Drèze and Murthi (2001), Huang and Xie (2013), and Yao et al. (2013). McNicoll (1984) formalized this line of reasoning (Post-Malthusian theory) by stressing that strong economic growth causes population growth either through increased birth rates or migration. Galor and Weil (1996, 2000), and Li and Zhang (2007) (also part of the Modern Growth theory) suggested a negative causal relationship running from economic growth to population. Galor and Weil (1996) claimed that since economic growth increases women's relative wages, the opportunity cost of raising children increases simultaneously with economic growth, thus reducing fertility, and population.

So overall, we can conclude that theoretically (and also empirically), causality, if it exists, between economic growth and population growth can run in both directions with either positive or negative signs. Thus, it is important for empirical researchers to formulate the relationship between economic growth and population growth in a causality-based framework, which treats both variables as potentially endogenous (see, Darrat and Al-Yousif, 1999; Thornton, 2001; Huang and Xie, 2013; Yao et al. 2013). It is also possible, however, that no causal relationships exist between these two variables. Given that the issue involving the relationship between population and economic growth remains inconclusive (Birdsall, et al. 2001), it is importance to revisit this question based on updated data and econometric methods.

3. Data and Hypotheses

3.1 Data

This study uses annual population and per capita real GDP for 21 countries over the period of 1870-2013. Both data sets (from 1870-2001) come from the accompanying data sets of "Two Thousand Years of Economic Statistics World Population, GDP and PPP" by Alexander V. Avakov (2010) and extended by the OECD data source from 2001-2013. Due to data availability, only 21 countries report such a long time series, 1870-2013.[2] Figures 1 and 2 plot the growth rates of per capita real GDP and population, respectively.[3] As Figures 1 and 2 illustrate, growth in the standard of living shows more volatility than population growth rates. Also, both variables exhibit sharp movements, especially toward the end of World War II.

3.2 Hypotheses

Our bivariate Granger causality tests between population and standard-of-living growth rates leads to four different outcomes with respect to causal effects. That is, population growth can Granger cause standard-of-living growth, or vice versa.[4] Also, each causality linkage can generate positive or negative effects. Of course, we can also observe the neutrality hypothesis, whereby no evidence exists of causality in either direction.

Table 1 reports the causality effects and their linkage to the Malthusian, Post-Malthusian, and Modern Growth models. The Malthusian model exhibits negative

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[2] The 21 countries include Austria, Belgium, Brazil, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sri Lanka, Sweden, Switzerland, the U.K., the U.S. and Uruguay. Researchers estimated growth regressions over the years that use a large number of variables to explain economic growth. In our case, however, the lack of continuous data on these variables over the entire sample period restricts our analysis to a bivariate model rather than a multivariate model.

[3] Summary statistics reveal that Japan and Uruguay experience the highest and lowest per capita real GDP growth rate of 2.4% and 1.1%, respectively. Brazil and France experience the highest and lowest mean population growth rate of 2.13% and 0.37%, respectively.

[4] We use POG to represent population growth and PEG to represent standard-of-living growth. That is, standard-of-living growth equals the growth rate of real GDP minus population growth.

Granger causality from population growth to standard-of-living growth and positive Granger causality from standard-of-living growth to population growth. The Modern Growth model reverses the effects, exhibiting positive Granger causality from population growth to standard-of-living growth and negative Granger causality from standard-of-living growth to population growth. The Post-Malthusian model possesses one leg in each of the other camps, exhibiting positive Granger causality from population growth to standard-of-living growth and positive Granger causality from standard-of-living growth to population growth.

4. Methodology

4.1. Bootstrap Panel Granger Causality Test

This paper applies the bootstrap panel causality method proposed by Kónya (2006) to measure the determinants of causality between population growth and standard-of-living growth. As emphasized by Kónya (2006),[5] the results of the bootstrap panel causality method unit-root and cointegration tests are all robust, which implies that we do not need to test all variables for stationarity (Kónya, 2006).[6] The robust feature of bootstrap panel causality arises from the generation of country-specific critical values from the bootstrapping method. Importantly, we use the levels of the variables in empirical analysis because differencing variables to make them stationary (i.e., using the difference form of variables) may lead to a loss of trend dynamics in the series.

The bootstrap panel causality approach of Kónya first requires estimating the described system by SUR to impose zero restrictions for causality by the Wald principle, and then requires generating bootstrap critical values. Since we use country-specific Wald tests with country-specific bootstrap critical values in the panel causality method, the Wald test does not require a joint hypothesis for all countries in the panel.

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[5] The alternative panel Granger causality test was developed by Hurlin (2008). The method, however, does not control for cross-sectional dependence, and only provide results for the full-sample.

[6] See Kónya (2006) for more details of the bootstrapping method and of country-specific critical values.

The equation system for panel causality analysis includes two sets of equations that are written as follows:

$$\begin{aligned}
PEG_{1,t} &= \alpha_{1,1} + \sum_{i=1}^{ly_1} \beta_{1,1,i} PEG_{1,t-i} + \sum_{i=1}^{lx_1} \delta_{1,1,i} POG_{1,t-i} + \varepsilon_{1,1,t} \\
PEG_{2,t} &= \alpha_{1,2} + \sum_{i=1}^{ly_1} \beta_{1,2,i} PEG_{2,t-i} + \sum_{i=1}^{lx_1} \delta_{1,2,i} POG_{2,t-i} + \varepsilon_{1,2,t} \\
&\vdots \\
PEG_{N,t} &= \alpha_{1,N} + \sum_{i=1}^{ly_1} \beta_{1,N,i} PEG_{N,t-i} + \sum_{i=1}^{lx_1} \delta_{1,N,i} POG_{1,N,t-i} + \varepsilon_{1,N,t}
\end{aligned} \tag{1}$$

and

$$\begin{aligned}
POG_{1,t} &= \alpha_{2,1} + \sum_{i=1}^{ly_2} \beta_{2,1,i} PEG_{1,t-i} + \sum_{i=1}^{lx_2} \delta_{2,1,i} POG_{1,t-i} + \varepsilon_{2,1,t} \\
POG_{2,t} &= \alpha_{2,2} + \sum_{i=1}^{ly_2} \beta_{2,2,i} PEG_{2,t-i} + \sum_{i=1}^{lx_2} \delta_{2,2,i} POG_{2,t-i} + \varepsilon_{2,2,t} \\
&\vdots \\
POG_{N,t} &= \alpha_{2,N} + \sum_{i=1}^{ly_2} \beta_{2,N,i} PEG_{N,t-i} + \sum_{i=1}^{lx_2} \delta_{2,N,i} POG_{N,t-i} + \varepsilon_{2,N,t}
\end{aligned} \tag{2}$$

In the systems of equations in (1) and (2), *PEG* refers to the indicator of per capita standard-of-living growth, *POG* denotes the indicator of population growth, *N* (=21) is the number of panel members, *t* is the time period *(t=1,…,T)*, and *l* is the lag length. Since, in this regression system, each equation has different predetermined variables and the error terms might be cross-sectionally correlated, we can view these sets of equations as a SUR system. To test for Granger causality in this system, alternative causal relations for each country may exist: (i) one-way Granger causality exists from *POG* to *PEG,* if not all $\delta_{1,i}$ are zero, but all $\beta_{2,i}$ are zero; (ii) one-way Granger causality exists from *PEG* to *POG,* if all $\delta_{1,i}$ are zero, but not all $\beta_{2,i}$ are zero; (iii) two-way Granger causality exists between *POG* and *PEG,* if neither $\delta_{1,i}$ nor $\beta_{2,i}$ are all zero; and (iv) no Granger causality exists between *POG* and *PEG,* if all $\delta_{1,i}$ and $\beta_{2,i}$ are zero.

Before proceeding with the estimation, we must determine the optimal lag lengths.[7] Since the results from the causality test may differ with different lag structures, determining the optimal lag length(s) is crucial for the robustness of the empirical findings. In a large panel system, lag lengths and numbers of independent variables can cause a substantial computational burden. Following Kónya (2006), maximal lags can differ across variables, but cannot differ across equations. In our paper, we estimate the regression system by each possible pair of ly_1, lx_1, ly_2, lx_2 lz_1, and lz_2, where we assume 1 to 8 lags exist, and then we choose the combinations that minimize the Schwarz Bayesian Criterion.[8]

4.2. Cross-Sectional Dependence Tests

One of the most important assumptions in the bootstrap panel causality method is the existence of cross-sectional dependence among the countries in the panel. In the case of cross-sectionally correlated errors, the estimator from the regression system described with the SUR is more efficient than the estimator from the pooled ordinary least squares (pooled OLS) model, because the country-by-country OLS approach does not consider cross-sectional dependence. Therefore, testing for cross-sectional dependence is the most crucial issue for the selection of an efficient estimator and, hence, for the panel causality results.

To test for cross-sectional dependence, the existing empirical literature uses extensively the Lagrange multiplier (LM) test by Breusch and Pagan (1980) . The LM test requires the estimation of the following panel data model:

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it} \quad \text{for} \quad i = 1, 2, ..., N; \quad t = 1, 2, ..., T \qquad (3)$$

In equation (3), y_{it} is per capita economic growth *(PEG)*, *i* is the cross-sectional dimension, *t*

[7] As indicated by Kónya (2006), this is an important step because the causality test results may depend critically on the lag structure. In general, lag decisions may cause different estimation results. Too few lags mean that some important variables are omitted from the model and this specification error will usually cause incorrect estimation in the retained regression coefficients, leading to biased results. On the other hand, too many lags will waste observations and this specification error will usually increase the standard errors of the estimated coefficients, leading to inefficient results. Based on Schwarz Bayesian Criterion, we find the optimal lag is 6 for our estimated model.

[8] To save space, we do not report the results from the lag selection procedure, but these results are available on request.

is the time dimension, x_{it} is $k \times 1$ vector of explanatory variable (i.e., Population growth (POG)), and α_i and β_i are the individual intercepts and slope coefficients, respectively, that can vary across countries.

In the LM test, the null hypothesis of no-cross sectional dependence, $H_0 : Cov(u_{it}, u_{jt}) = 0$, for all t and $i \neq j$ is tested against the alternative hypothesis of cross-sectional dependence, $H_1 : Cov(u_{it}, u_{jt}) \neq 0$, for at least one pair of $i \neq j$. In order to test the null hypothesis, Breusch and Pagan (1980) developed the LM test:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \quad , \tag{4}$$

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals from the pooled OLS estimation of equation (3) for each i. Under the null hypothesis, the LM statistic exhibits an asymptotic chi-square statistic with $N(N-1)/2$ degrees of freedom. Note that the LM test is valid for a relatively small N and a sufficiently large T. In the case of large panels, for example, where $T \to \infty$ first and then $N \to \infty$, Pesaran (2004) proposed a scaled version of the LM test:

$$CD_{lm} = \left(\frac{1}{N(N-1)} \right)^{1/2} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T \hat{\rho}_{ij}^2 - 1) . \tag{5}$$

Under the null hypothesis, the CD_{lm} test converges to the standard normal distribution.

The CD_{lm} test, however, may be subject to substantial size distortions when N is large and T is small. Pesaran (2004) developed a more general cross-sectional dependence test that is valid for large panels. This CD test is:

$$CD = \sqrt{\left(\frac{2T}{N(N-1)} \right)} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right). \tag{6}$$

Under the null hypothesis, the CD test exhibits an asymptotic standard normal distribution.

Pesaran (2004) indicated that the CD test has a mean that is exactly zero for fixed T and N, and is robust for heterogeneous dynamic models that include multiple breaks in slope coefficients and error variances, as long as the unconditional means of y_{it} and x_{it} are time-invariant and their innovations possess symmetric distributions. The CD test, however, will lack power in certain situations in which the population average pair-wise correlations are zero, but the underlying individual population pair-wise correlations are non-zero (Pesaran et al., 2008). Pesaran et al. (2008) proposed a bias-adjusted test, which is a modified version of the LM test. It uses the exact mean and variance of the LM statistic. The bias-adjusted LM test is as follows:

$$LM_{adj} = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{v_{Tij}^2}} \quad . \tag{7}$$

In equation (7), μ_{Tij} and v_{Tij}^2 are the exact mean and variance of $(T-k)\hat{\rho}_{ij}^2$, respectively, that are provided by Pesaran et al. (2008). Under the null hypothesis where T→∞ first and then N→∞, the LM_{adj} test is asymptotically distributed as a standard normal distribution.

4.3. Slope Homogeneity Tests

The second important aspect of the bootstrap panel causality approach is testing for cross-country heterogeneity. We apply the Wald principal to test the null hypothesis of slope coefficient homogeneity against the alternative hypothesis. The Wald principle is valid for all cases where the cross-sectional dimension (*N*) is relatively small and the time dimension (*T*) of the panel is large,[9] the explanatory variables are strictly exogenous, and the error variances are homoscedastic. Swamy (1970) developed the slope homogeneity test to detect cross-sectional heteroscedasticity (Pesaran and Yamagata, 2008). Pesaran and Yamagata (2008) proposed a standardized version of Swamy's test (also called the $\tilde{\Delta}$ test) for testing slope homogeneity in large panels. The $\tilde{\Delta}$ test is valid as $(N,T) \to \infty$ without any

[9] T > N is the basic requirement for our bootstrap panel causality test.

restrictions on the relative expansion rates of N and T when the error terms are normally distributed. In the $\tilde{\Delta}$ test approach, the first step computes the following modified version of Swamy's test:

$$\tilde{S} = \sum_{i=1}^{N} \left(\widehat{\beta}_i - \tilde{\beta}_{WFE} \right)' \frac{x_i' M_\tau x_i}{\tilde{\sigma}_i^2} \left(\widehat{\beta}_i - \tilde{\beta}_{WFE} \right), \tag{8}$$

where $\widehat{\beta}_i$ is the estimator from the pooled OLS, $\tilde{\beta}_{WFE}$ is the estimator from the weighted fixed effect pooled estimation of the regression model in equation (3), M_τ is an identity matrix, and $\tilde{\sigma}_i^2$ is the estimator of σ_i^2.[10] The standardized dispersion statistic is then defined as

$$\tilde{\Delta} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}} \right). \tag{9}$$

Under the null hypothesis with the condition of $(N,T) \to \infty$, so long as $\sqrt{N}/T \to \infty$ and the error terms are normally distributed, the $\tilde{\Delta}$ test has an asymptotic standard normal distribution. We can improve the small sample properties of the $\tilde{\Delta}$ test under normally distributed errors by using the following bias-adjusted version:

$$\tilde{\Delta}_{adj} = \sqrt{N} \left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{it})}{\sqrt{\mathrm{var}(\tilde{z}_{it})}} \right), \tag{10}$$

where the mean is $E(\tilde{z}_{it}) = k$ and the variance is $\mathrm{var}(\tilde{z}_{it}) = 2k(T-k-1)/T+1$.

5. Results and policy implications

5.1. Cross-sectional dependence and slope homogeneity

As we outlined earlier, testing for the cross-sectional dependence and slope homogeneity in the bootstrap panel causality analysis is crucial for selecting the appropriate estimator and for imposing restrictions for causality because countries that are highly integrated due to a high degree of globalization in economic or financial relations. Therefore, our empirical study

[10] To save space, see Pesaran and Yamagata (2008) for the details of Swamy's test and the estimators described in equation (8).

starts by examining the possible existence of cross-sectional dependence and heterogeneity across the countries in our sample. To investigate the existence of cross-sectional dependence, we carry out four different tests (CD_{BP}, CD_{lm}, CD, and LM_{adj}), that are presented in Table 2. We reject the null of no cross-sectional dependence at the conventional levels of significance, implying that the SUR method is more appropriate than country-by-country OLS estimation, which is assumed in the bootstrap panel causality approach. This finding implies that a shock occurring in one country appears to get transmitted to other countries. The existence of cross-sectional dependency also implies that examining causal linkages between population and standard-of-living growth in these countries requires that we consider this dependency in the causality regressions. In the presence of cross-sectional dependency, the SUR approach is more efficient than the country-by-country ordinary least-squares (OLS) method (Zellner, 1962). Therefore, the causality results obtained from the SUR estimator developed by Zellner (1962) will be more reliable than those obtained from the country-specific OLS estimations.

In Table 2, we also report the results from the slope homogeneity tests of Pesaran and Yamagata (2008). Three tests ($\tilde{\Delta}$, $\tilde{\Delta}_{adj}$, and Swamy Shat) all reject the null hypothesis of slope homogeneity, supporting country-specific heterogeneity, with the exception of the test of $\tilde{\Delta}_{adj}$. This rejection implies that a panel causality analysis that imposes a homogeneity restriction on the variable of interest results in misleading inferences. Therefore, the direction of causal linkages between population growth and standard-of-living growth may differ across the selected countries.

Both the cross-sectional dependency and the slope heterogeneity across the 21 countries provide evidence for the suitability of the bootstrap panel causality approach.

5.2. Causality

We report the empirical results from the bootstrap panel Granger causality analysis in Tables

3 and 4.[11] These empirical findings support four major policy implications. First, in Canada, Germany, Japan, Norway, and Switzerland, we find evidence of one-way Granger causality running from standard-of-living growth to population growth. If we examine the signs of the effects, we find that in Canada, Norway, and Switzerland, positive effects exist, indicating that for these three countries standard-of-living growth exerts a positive effect on population growth. On the contrary, we find a negative effect in Germany and Japan. In these two countries, standard-of-living growth exerts a negative effect on population growth. That is, a higher standard-of-living causes people to enjoy a wealthier life style and to desire fewer children, causing fertility reductions.

Second, evidence shows one-way Granger causality running from population growth to standard-of-living growth in Finland, France, Portugal, and Sweden, indicating that population growth does affect standard-of-living growth. If we examine the signs of the coefficients, however, we find that Finland, Portugal, and Sweden experience negative effects. That is, for these three countries, population growth exerts a negative effect on standard-of-living growth, which supports the arguments of Malthus (1798), where population growth decreases per capita output, because output growth cannot keep up the at the same pace. To keep the natural balance between population, food, and consumption, preventive checks (i.e. fertility reduction) and positive checks (i.e. mortality increase) on population growth are necessary (Malthus, 1798). On the contrary, we find the sign of the effect in France is positive. This result indicates that for France, population growth exerts a positive effect on standard-of-living growth, which supports the arguments of the Kremer (1993). Kremer (1993) has empirically confirmed that a larger population associates with higher population growth rates and faster technological improvement. That is, technological

[11] The reader is referred to Kónya (2006) for explanations of the bootstrap procedure and how the country-specific critical values are generated. Note that the sign of the causal effect is derived from the sum of the coefficients of the variable considered as independent in a specific equation. So in our case, the sign is based on the sum of the coefficients on the six lags of the causal variable.

development results from population growth, which leads to an increase of labor productivity, per capita income, and improvement in living standards.

Third, we find bidirectional Granger causality between population growth and standard-of-living growth in both Austria and Italy. For these two countries, population growth and standard-of-living growth both are endogenous, indicating that they mutually influence each other. Their mutual reinforcement has important implications for the conduct of standard-of-living or population growth policies. If we examine the signs of the effects, we find that for Italy, population growth exerts a positive effect on standard-of-living growth. But, standard-of-living growth exerts a negative effect on population growth. The positive effect of population growth on standard-of-living growth further supports the arguments of the Kremer (1993). If we examine the signs of the effect in Austria, we find that population growth exerts a negative effect on standard-of-living growth, and standard-of-living growth exerts a negative effect on population growth. The negative effect of population growth on standard-of-living growth further supports the arguments of the Malthus (1798). These results demonstrate that rapid population growth is a problem in Austria, because it contributes to lower investment growth and diminishes the savings rate. Policy makers in Austria can address these serious standard-of-living consequences of rapid population growth by investing in family planning services. Development of independent media and liberal education in educational institutions may in time also help by encouraging a smaller family size.

Finally, we find no causal relationship between population growth and standard-of-living growth in Belgium, Brazil, Denmark, Netherlands, New Zealand, Spain, Sri Lanka, the UK, the USA, and Uruguay. These results support the neutrality hypothesis for the population-income nexus, which indicates that population growth and standard-of-living growth do not influence each other.

5.3. Robustness check

Since our sample is quite long with economies undergoing tremendous transition both in terms of standard-of-living growth and population growth, we took cross-sectional averages for both standard-of-living and population growth rates and applied the CUSUM test to the two time series of averages across the 21 countries. We find a structural break in 1952, which is not surprising given the high growth rates in both population and GDP witnessed after World War II. Therefore, we divided the total sample into two sub-sample periods, 1871-1951 and 1952-2013, to perform a robustness check.[12]

We report the 1871-1951 results in Tables 5 and 6 and the 1952-2013 results in Tables 7 and 8. Based on the empirical results from Tables 5 and 6, we find that population growth Granger cause standard-of-living growth for Finland and France. We also find a relationship from standard-of-living growth to population growth for Denmark, Japan, and Norway and bidirectional causality between population growth and standard-of-living growth for both Austria and Italy. For the rest of 14 countries (i.e., Belgium, Brazil, Canada, Germany, Netherlands, New Zealand, Portugal, Spain, Sri Lanka, Sweden, Switzerland, the UK, the USA, and Uruguay), we find no causality between population growth and standard-of-living growth.

If we look at the sign of the coefficients from Table 5 for 1870-1951, we see that population growth exerts a significant negative effect on standard-of-living growth for Finland. For France, we find that population growth exerts a significant positive effect on standard-of-living growth. In Table 6, we also find that standard-of-living growth exerts a

[12] Multiple other break dates exists, as rightly pointed out by an anonymous referee, in both the standard of living and population growth rate equations, based on the CUSM and Bai and Perron (2003) tests of structural breaks applied to each of the 21 countries separately– details of which are available on request. The approach that we undertake, however, does not allow us to model breaks using dummy variables (as suggested by the referee). Hence, we had to rely on the break determined by the CUSUM test based on cross-sectional averages. Using the Bai and Perron (2003) test on the cross-sectional averages also identified multiple structural breaks. But, we could not split our samples, since some of the sub-samples would imply that T is no longer greater than N, and would make the Kónya (2006) approach infeasible. In such a situation, an ideal methodology to pursue would be time-varying causality. Time-varying causality, however, is currently restricted to only time-series data. Hence, while our panel approach allows us to analyze causality for each of the cross-sectional units explicitly, unlike standard panel data approaches that provide an overall estimate for the panel, the inability to model breaks using dummy variables can be considered as a drawback of our approach.

significant negative effect on population growth for both Denmark and Japan. For Norway, we find that standard-of-living growth exerts a positive effect on population growth. For Austria and Italy, bidirectional causality exists between population growth and standard-of-living growth. The signs of the effects differ. On one hand, we find that population growth exerts a positive effect on standard-of-living growth; but, standard-of-living growth exerts a negative effect on population growth in Italy. For Austria, on the other hand, we find that population growth exerts a negative effect on standard-of-living growth, and standard-of-living growth also exerts a negative effect on population growth.

We report the results for 1952-2013 in Tables 7 and 8. For this time period, we find that population growth Granger causes standard-of-living growth only for Sri Lanka and that standard-of-living growth Granger causes population growth for Belgium, Denmark, France, Germany, New Zealand, Spain, Switzerland, and Uruguay. We also find bidirectional causality between population growth and standard-of-living growth only for Japan. For the other 11 countries (i.e., Austria, Brazil, Canada, Finland, Italy, Netherlands, Norway, Portugal, Sweden, the UK, and the USA), we find no causality between population growth and standard-of-living growth.

If we examine the signs of the effects for Sri Lanka, we see a negative effect from population growth to standard-of-living growth. An opposite relationship from standard-of-living growth to population growth exists for Belgium, Denmark, France, Germany, New Zealand, Spain, Switzerland, and Uruguay. We find that the signs of the effects for all countries are significantly positive, with the exception of Uruguay. Looking at the effects in both equations for Japan, we find that population growth exerts a positive effect on standard-of-living growth and standard-of-living growth also exerts a positive effect on population growth.[13]

5.4. Policy Conclusions

The robustness check, based on structural breaks, is not only important statistically, but is of paramount importance when it comes to policy recommendations. From a pure statistical point of view, the full-sample results cannot be completely relied upon in the presence of structural breaks (for a detailed discussion in this regard, refer to Balcilar et al., (2014)). That is, the assumption that the parameter estimates of the model are constant over the entire sample, upon which the Granger causality test relies upon, is violated. Hence, in our case, it makes sense to provide policy prescriptions based on the more recent sub-sample, namely: 1952-2013. For Japan, to improve the standard of living, population growth should increase, as these variables are positively related. And this process is likely to be sustainable, since higher per capita growth rate also leads to higher population growth rates for Japan, given the evidence of positive bi-directional causality in Japan. In Sri Lanka, however, population growth needs to be curtailed if one wants to promote the standard of living. For rest of the 21 countries, no evidence of significant causal relationship running from population growth rate to standard of living exists. The positive (negative) causality that was observed for Finland, France, and Italy (Austria), in the first sub-sample (1870-1952), running from population growth to standard of living growth, does not carry over to more recent periods. When

[13] As suggested by an anonymous referee, we conducted the analysis for the full-sample, as well as the sub-samples by dropping Uruguay and Sri Lanka from our panel of 21 countries. For the 19 countries considered, the results for the sub-samples were virtually the same for the 21 countries. The only exceptions were that under the null that population growth does not Granger cause standard-of-living growth, we could not reject the null hypothesis for Austria and Finland. The differences between the 19 country case and the 21 country case were quite stark when we dropped Uruguay and Sri Lanka from the full-sample. Under the null that population growth (standard-of-living growth) does not Granger cause standard-of-living growth (population growth), we rejected the null hypothesis for only 3 (2) countries, namely Austria, Italy and the Netherlands (Italy and New Zealand). We believe that the weak results for the full-sample could reflect the existence of cross-sectional dependence between the 21 countries (i.e., with Uruguay and Sri Lanka included). Further, note that it is quite well-accepted that panel data results are sensitive to the cross-sectional units chosen, since there selection bias may exist. This is specifically why, we did not choose countries based on certain pre-conceived categorization, but went with these 21 countries for which data were available over the entire sample period of 1871-2013. But having said this, it is also true that Granger causality tests are sensitive to structural breaks. So, when we rely on the sub-sample analysis, our results are consistent for the included countries across the 19 and 21 countries cases.

causality runs from standard of living growth to population growth, the positive relationships in Belgium, Denmark, France, Germany, Japan, New Zealand, Spain and Switzerland confirm Malthus' (1798) second proposition and the Post-Malthusian theories. Since barring Japan, the causality is only one way, these countries should ensure that standard of living growth does not grow population to quickly, which might lead to Malthus' (1798) first proposition, which would hamper standard of living growth. Interestingly for Uruguay, higher standard-of-living growth has curtailed population growth and supports the Modern Growth Theory. As long as the lower population growth does not imply lower growth in human capital, Uruguay can still sustain its standard of living. Otherwise, this negative relationship may affect growth of per capita real GDP in the future. When compared to the first-sub-sample, barring Denmark and Japan, the causal relationship disappears for Austria, Italy, and Norway in the recent sub-sample. Interestingly, while negative causality was observed for all countries barring Norway in the first sub-sample, Denmark and Japan exchange signs in the recent sub-sample, indicating that while standard-of-living growth used to hamper population growth, it now plays a positive role in population growth. Based on the recent sub-sample, for the remaining eleven countries (Austria, Brazil, Canada, Finland, Italy, Netherlands, Norway, Portugal, Sweden, UK and USA), the neutrality hypothesis holds, implying that population growth neither improves nor deteriorates standard-of-living growth. In other words, these countries would need to rely on other sources, such as technological advances, to ensure standard-of-living growth. Given this list of industrial countries (except the emerging market Brazil), the lack of causality makes sense, since these economies rely mainly on technological progress to sustain their standard-of-living growth.

6. Conclusions

This study applies the bootstrap panel causality test proposed by Kónya (2006) to test the causal link between population growth and standard-of-living growth in 21 countries over the period of 1870-2013. The bootstrap panel causality test, which accounts for dependency and heterogeneity across countries, supports evidence on the direction of causality. Regarding the population growth-standard-of-living growth nexus, we find one-way Granger causality running from population growth to standard-of-living growth for Finland, France, Portugal, and Sweden; one-way Granger causality running from standard-of-living growth to population growth for Canada, Germany, Japan, Norway, and Switzerland; and no causal relationship between population growth and standard-of-living growth in Belgium, Brazil, Denmark, Netherlands, New Zealand, Spain, Sri Lanka, the UK, the USA and Uruguay. Furthermore, we find feedback between population growth and standard-of-living growth for Austria and Italy.

Due to a structural break in 1952, we also divided the sample into two subsamples, which leads to conflicting results. For the period of 1871-1951, we find that population growth Granger causes standard-of-living growth for Finland and France; standard-of-living growth causes population growth for Denmark, Japan, and Norway; and bidirectional causality exists between population growth and standard-of-living growth for both Austria and Italy. For the more recent time period of 1952-2013, we find that population growth Granger causes standard-of-living growth only for Sri Lanka; that standard-of-living growth Granger causes population growth for Belgium, Denmark, France, Germany, New Zealand, Spain, Switzerland, and Uruguay; and that bidirectional causality exists between population growth and standard-of-living growth only for Japan.

Due to the differences in the existence and direction of causality between countries and across time periods, our results provide important policy implications for these 21 countries. We must view our results with some caution as well. Note that our panel VAR approach is atheoretical in nature. It just captures the underlying dynamics of the data, and does not specify a proper theoretical framework that can explicitly pinpoint the underlying reasons behind the existence and non-existence of the relationships or the sign of that relationship. While analyzing data over 1871-2013 comes with the advantage of tracking the developmental process of these countries based on a long span of data, the disadvantage is that we cannot choose additional variables (which is in line with a comprehensive theoretical framework justifying the relationship between standard of living growth and population growth), due to lack of data on other series over the entire period of study. Hence, some of the obtained results could become weaker in the presence of relevant variables, like capital formation. This is an interesting avenue of future research, but might entail looking at a shorter sample.

References

Afzal, M. (2009). Population growth and economic development in Pakistan, *The Open Demography Journal*, 2, 1-17.

Avakov, Alexander V. (2010). Two Thousand Years of Economic Statistics: World Population, GDP and PPP, Algora Publishing.

Bai, J., and Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1), 72–78.

Birdsall, N.; Allen C. Kelley; and Steven W. Sinding (2001 eds.): *Population Matters: Demographic Change, Economic Growth, and Poverty in the Developing World*. New York: Oxford University Press.

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange Multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies*, 47(1), 239-253.

Cassen, R. (1976) Population and development: a survey, *World Development*, 4, 785-830.

Darrat, A. F, Al-Yousif, Y. K. (1999). On the long-run relationship between population and economic growth; some time series analysis evidence for developing countries, *Eastern Economic Journal*, 25, 310-312.

Dasgupta, P. (2000). Population and Resources: An Exploration of Reproductive and Environmental Externalities. *Population and Development Review*, 26: 643–689.

Drèze, J. and Murthi, M. (2001). Fertility, Education, and Development: Evidence from India. *Population and Development Review*, 27: 33–63.

Easterlin, Richard A. (1967). Effects of Population Growth on the Economic Development of 18 Developing Countries. *Annals of the American Academy of Political and Social Science* 369:98-108.

Espenshade, Thomas J. (1978). Zero Population Growth and the Economies of Developed Nations. *Population and Development Review* 4, no. 4: 645-680.

Galor, O., Weil D. (1996). The gender gap, fertility, and growth, *American Economic Review*, 86, 374-387.

Galor, O., Weil D. (2000). Population, technology and growth: from Malthus stagnation to the demographic transition and beyond, *American Economic Review*, 90, 806-828.

Huang, T-H., Xie Zixiong. (2013). Population and economic growth: a simultaneous equation perspective, *Applied Economics*, 45, 3820-3826.

Hurlin, C. (2008). Testing for Granger Non Causality in Heterogeneous Panels, Mimeo. Department of Economics: University of Orleans.

Kónya, L. (2006). Exports and growth: Granger causality analysis on OECD countries with a panel data approach. *Economic Modelling*, 23, 978–992.

Kremer, Michael. (1993). Population Growth and Technological Change: One Million B.C. to 1990. *The Quarterly Journal of Economics* 108, no.3:681

Kuznets, S. (1955). *Economic Growth and Income Inequality*. *American Economic Review*. (March). 45(1): 1-28

Kuznets, Simon. (1976). Demographic aspects of the size distribution ofincome. *Economic Development and Cultural Change* 25, no. 1 (October):1-94.

Kuznets, Simon, Richard E. Quandt, and Milton Friedman. (1960). Population Change and AggregateOutput. In *Demographic and Economic Change in Developed Countries, Universities*- National Bureau, I:340 - 367. New York: National Bureau of Economic Research.

Li, H, Zhang, J. (2007). Do high birth rates hamper economic growth? *Review of Economics and Statistics*, 30, 67-80.

Luigi Palumbo, Ferrara Alberto, Varra Pasquale. (2010). Population and Economic Growth: Evidence from EU and Emerging Countries, Gottingen Summer School 2010, Relations between the EU and the emerging global players.

Malthus, T.R. (1798). An Essay on the Principle of Population, J. Johnson, London.

Mason, Andrew. (1988). Saving, Economic Growth, and Demographic Change. *Population and Development Review* 14, no. 1: 113-144.

McNicoll, G. (1984). Consequences of rapid population growth: an overview and assessment, *Population and Development Review*, 10, 177-240.

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. Cambridge Working Papers in Economics No. 0435, Faculty of Economics, University of Cambridge.

Pesaran, M. H., Ullah, A., & Yamagata, T. (2008). A bias-adjusted LM test of error cross-section independence. *Econometrics Journal* 11, 105–127.

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, 142, 50–93

Simon, Julian L. (1987). *Population Growth, Economic Growth and Foreign Aid*. *Cato Journal (*Spring/summer) 7(1): 159-193.

Solow, Robert M. (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics* 70, no. 1: 65.

Swamy, P. A. V. B. (1970). Efficient inference in a random coefficient regression model. *Econometrica*, 38, 311-323.

Thornton, J. (2001). Population growth and economic growth: long-run evidence from Latin America, *Southern Economic Journal*, 68, 464-468.

Todaro, M.P. and Smith, S.C. (2006). *Economic Development*. *London*: Pearson Education

Toney, Michael B., William F. Stinner, and Yun Kim. (1981). The Population Debate: A Survey of Opinions of a Professional Organization's Membership. *Population and Environment* 4, no. 3:156-173.

Yao, W., Kinugasa, T., Hamori, S. (2013). An empirical analysis of the relationship between economic development and population growth in China, *Applied Economics,* 45, 4651-4661,

Zellner A. (1962). An efficient method of estimating seemingly unrelated regression equations and tests of aggregation bias. *Journal of the American Statistical Association*, 57, 500-509.

Table 1: Granger Causality and Malthusian, Post-Malthusian, and Modern Growth Models

	n Granger causes (g-n)	(g-n) Granger causes n
Negative	Malthusian	Modern Growth
Positive	Post-Malthusian & Modern Growth	Malthusian & Post-Malthusian

Note: The growth rate of population and output equal n and g, respectively. Thus, the growth of output per capita equals (g-n).

Table 2. Cross-sectional Dependence and Homogeneous Tests

CD_{BP}	1619.376***
CD_{LM}	68.770***
CD	24.294***
LM_{adj}	67.684***
$\tilde{\Delta}$	12.824***
$\tilde{\Delta}_{adj}$	0.091
Swamy Shat	104.108***

Note: 1. ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

Table 3. Population Growth does not Granger Cause Standard of Living Growth

Country	Coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
Austria	-1.626	**7.129****	3.606	5.101	11.930
Belgium	-0.355	0.671	3.488	5.243	9.752
Brazil	0.754	1.123	3.508	5.442	11.975
Canada	-0.102	0.076	3.657	5.078	8.896
Denmark	-0.240	0.190	3.415	4.322	8.709
Finland	-0.863	**3.581***	3.353	4.974	9.197
France	1.969	**15.835*****	3.974	5.436	9.237
Germany	0.430	0.649	3.470	6.170	19.869
Italy	3.512	**15.883*****	3.534	5.098	9.444
Japan	0.624	0.709	3.486	5.099	8.462
Netherlands	1.071	2.538	3.336	5.048	11.808
N. Zealand	-0.342	1.012	3.711	5.124	8.514
Norway	-1.019	2.437	3.881	5.409	8.731
Portugal	-1.746	**8.968*****	3.647	5.566	8.878
Spain	-0.314	0.090	3.813	5.435	9.125
Sri Lanka	-0.074	0.027	3.455	4.826	8.552
Sweden	-1.417	**5.114****	3.533	5.093	9.414
Switzerland	-0.147	0.112	3.909	5.532	9.729
UK	-0.128	0.214	3.918	5.730	12.121
USA	-0.511	0.561	3.754	5.212	8.706
Uruguay	-0.693	1.996	3.489	5.146	8.036

Note: ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. Bootstrap critical values are obtained from 10,000 replications.

Table 4. Standard of Living Growth does not Granger Cause Population Growth

Country	Coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
Austria	-0.034	**87.594*** **	2.951	5.009	25.490
Belgium	-0.001	0.009	3.861	5.554	9.003
Brazil	-0.002	0.582	3.888	5.520	14.982
Canada	0.017	**4.267***	3.664	5.698	9.578
Denmark	-0.001	0.887	3.738	5.377	9.229
Finland	0.005	0.358	3.622	5.249	9.617
France	0.003	0.333	3.782	6.209	12.340
Germany	-0.019	**8.657** **	3.038	5.323	18.219
Italy	-0.010	**15.202*** **	3.634	5.329	9.485
Japan	-0.017	**27.530*** **	2.856	4.319	17.360
Netherlands	0.005	1.201	2.983	6.110	24.362
N. Zealand	0.010	2.898	3.664	5.304	9.042
Norway	0.007	**7.723** **	3.663	5.552	8.754
Portugal	-0.003	0.296	2.981	5.546	11.420
Spain	0.001	0.505	3.660	5.673	10.403
Sri Lanka	0.015	2.265	3.769	5.803	9.981
Sweden	0.005	2.455	3.419	5.759	9.388
Switzerland	0.016	**6.122** **	3.699	5.013	8.616
UK	0.026	2.390	3.094	4.618	9.393
USA	0.003	1.699	3.774	5.404	9.376
Uruguay	0.010	1.353	3.453	5.020	9.698

Note: ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. Bootstrap critical values are obtained from 10,000 replications.

Table 5. Population Growth does not Granger Cause Standard of Living Growth: 1871-1951

Country	Coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
Austria	-1.927	**6.324***	5.177	8.080	21.443
Belgium	0.291	0.241	5.388	7.880	14.319
Brazil	-0.425	0.109	3.901	6.542	21.520
Canada	-0.543	0.880	4.931	7.054	13.450
Denmark	0.755	0.327	5.022	6.756	11.076
Finland	-1.468	**5.279***	5.016	6.825	12.088
France	2.959	**18.235*****	5.242	8.177	14.039
Germany	0.863	1.519	4.333	7.625	18.565
Italy	6.503	**19.964*****	4.864	7.652	15.285
Japan	0.693	0.231	4.729	6.857	14.566
Netherlands	1.662	2.509	5.994	9.874	21.039
N. Zealand	-0.050	0.010	4.711	6.691	11.873
Norway	-0.524	0.360	4.856	7.509	12.821
Portugal	-0.464	0.133	5.062	6.778	11.288
Spain	0.439	0.035	4.508	6.649	13.012
Sri Lanka	0.738	1.136	5.046	7.750	12.899
Sweden	-1.601	2.657	5.010	7.637	12.899
Switzerland	-0.767	0.911	4.073	5.876	12.362
UK	-0.219	0.462	4.670	7.367	15.465
USA	-0.323	0.091	4.914	6.379	9.868
Uruguay	-0.765	0.685	4.566	6.663	11.849

Note: ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. Bootstrap critical values are obtained from 10,000 replications.

Table 6. Standard of Living Growth does not Granger Cause Population Growth 1871-1951

Country	Coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
Austria	-0.035	**68.683*** **	4.118	7.927	38.346
Belgium	-0.002	0.139	4.109	6.174	11.873
Brazil	-0.003	0.613	5.217	7.509	13.373
Canada	0.016	4.056	5.308	7.512	13.269
Denmark	-0.005	**5.916***	4.853	6.836	11.843
Finland	0.010	0.777	4.769	6.891	12.589
France	0.001	0.038	4.482	6.845	15.605
Germany	-0.017	4.327	5.197	8.899	28.078
Italy	-0.010	**9.988****	4.662	6.998	11.324
Japan	-0.014	**8.909****	4.159	6.824	24.899
Netherlands	0.012	3.894	4.000	7.184	21.778
N. Zealand	0.012	1.404	4.854	6.852	14.624
Norway	0.007	**5.415***	5.075	7.045	10.885
Portugal	-0.001	0.626	4.730	7.420	12.935
Spain	-0.001	0.113	6.006	8.304	18.267
Sri Lanka	0.012	0.809	4.527	6.347	12.162
Sweden	0.001	0.309	5.188	6.878	11.432
Switzerland	0.011	3.222	4.955	7.511	16.406
UK	0.032	1.961	5.229	7.413	12.059
USA	0.003	1.260	4.702	6.583	12.764
Uruguay	0.007	2.495	4.761	6.864	12.547

Note: ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. Bootstrap critical values are obtained from 10,000 replications.

Table 7. Population Growth does not Granger Cause Standard of Living Growth: 1952-2013

Country	Coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
Austria	-0.114	0.071	6.484	9.778	19.342
Belgium	-0.099	0.028	7.112	10.418	18.439
Brazil	1.246	3.020	5.668	8.680	16.044
Canada	0.485	3.666	6.157	8.790	14.026
Denmark	-0.549	0.382	6.114	9.335	17.384
Finland	0.050	0.003	6.491	9.242	16.660
France	0.431	1.507	7.425	10.782	18.791
Germany	-0.430	0.797	5.951	8.151	14.152
Italy	1.063	2.131	5.971	8.080	14.980
Japan	2.102	**7.667***	5.713	8.553	15.549
Netherlands	1.010	2.782	5.239	7.682	12.572
N. Zealand	0.264	0.396	5.212	7.389	13.716
Norway	0.834	0.623	5.155	7.650	15.486
Portugal	-0.410	0.715	6.598	10.019	18.694
Spain	-0.280	0.245	7.086	10.010	15.677
Sri Lanka	-1.115	**6.825***	5.311	7.336	14.025
Sweden	-0.939	2.710	6.314	9.260	16.426
Switzerland	-0.053	0.036	6.198	9.030	15.324
UK	-0.431	0.347	5.819	7.893	13.355
USA	0.263	0.239	6.674	9.125	16.949
Uruguay	1.375	3.736	5.151	7.906	14.646

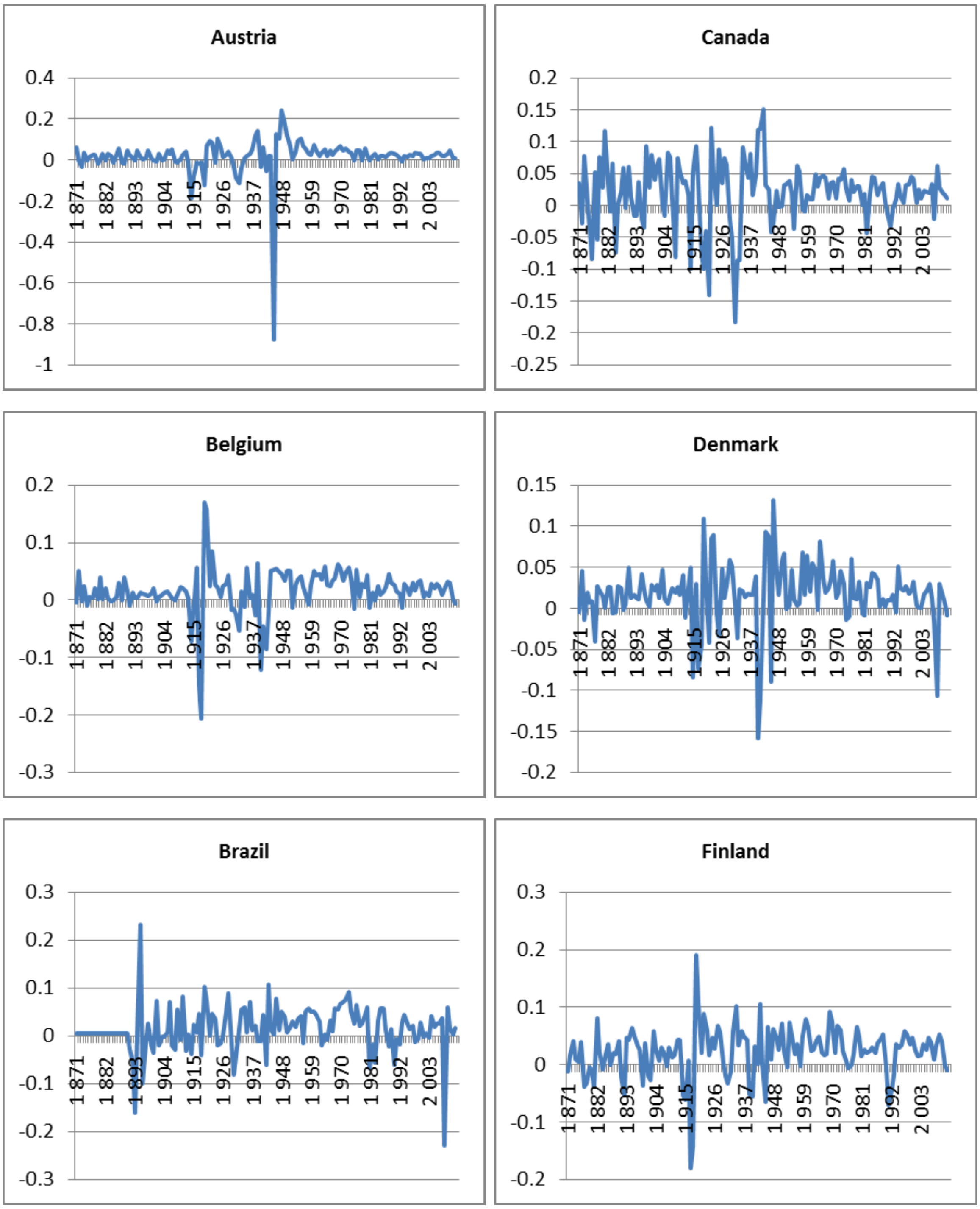
Note: ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. Bootstrap critical values are obtained from 10,000 replications.

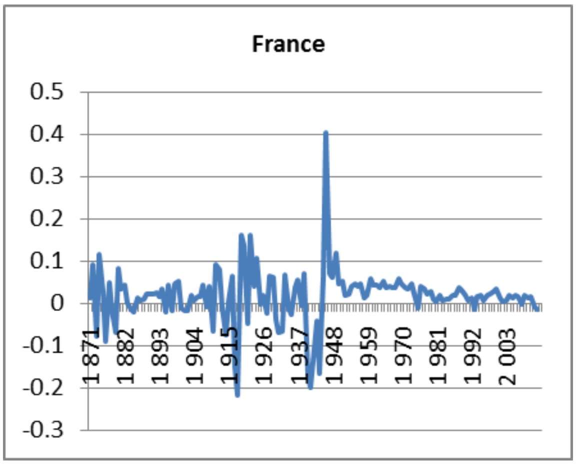
Table 8. Standard of Living Growth does not Granger Cause Population Growth: 1952-2013

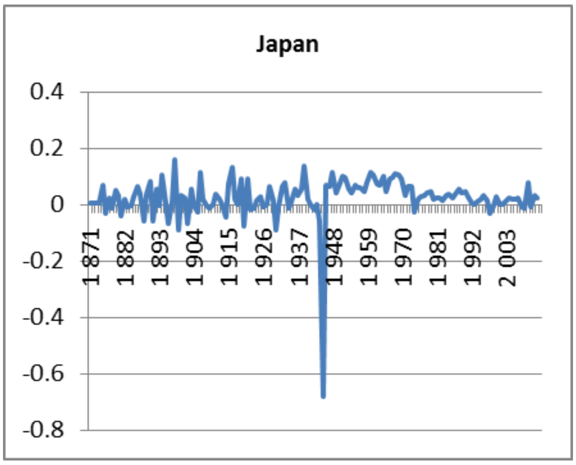
Country	Coefficient	Wald Statistics	Bootstrap Critical Value		
			10%	5%	1%
Austria	0.019	5.131	6.233	8.803	16.088
Belgium	0.017	**9.003****	5.690	8.045	14.647
Brazil	0.001	1.892	6.403	9.158	16.981
Canada	0.041	1.971	5.055	7.337	13.362
Denmark	0.012	**19.313*****	5.776	8.384	14.026
Finland	-0.000	0.002	6.529	9.459	17.364
France	0.034	**7.147***	5.617	7.614	13.938
Germany	0.030	**20.924*****	5.810	8.784	15.430
Italy	0.004	1.359	7.289	10.338	16.922
Japan	0.011	**18.190****	8.086	11.176	19.056
Netherlands	0.008	3.372	6.626	8.866	14.830
N. Zealand	0.028	**5.832***	5.490	7.582	13.988
Norway	0.006	3.680	6.564	9.573	18.374
Portugal	0.001	0.020	6.142	8.924	15.772
Spain	0.007	**11.986****	6.869	10.275	18.283
Sri Lanka	-0.007	1.799	6.419	9.083	15.477
Sweden	0.014	3.171	6.330	9.079	16.346
Switzerland	0.049	**13.885****	6.328	9.001	19.226
UK	0.010	4.389	6.140	8.518	14.227
USA	-0.004	0.619	6.087	8.852	16.195
Uruguay	-0.051	**7.866***	6.151	7.964	14.151

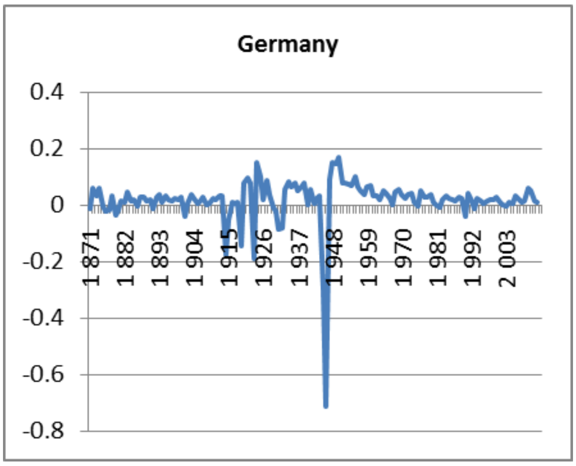
Note: ***, **, and * indicate significance at the 0.01, 0.05 and 0.1 levels, respectively. Bootstrap critical values are obtained from 10,000 replications.

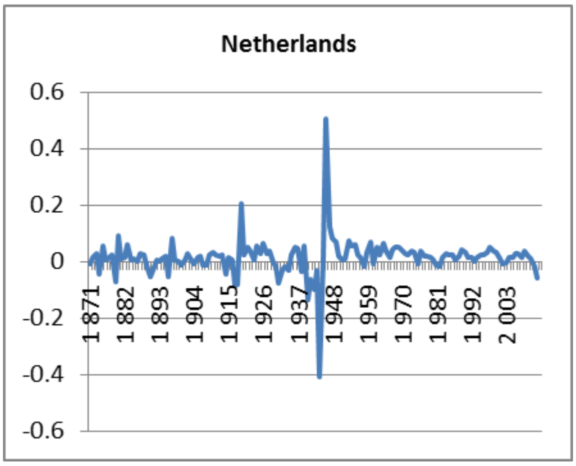
Figure 1: Plots of Standard of Living Growth Rates:

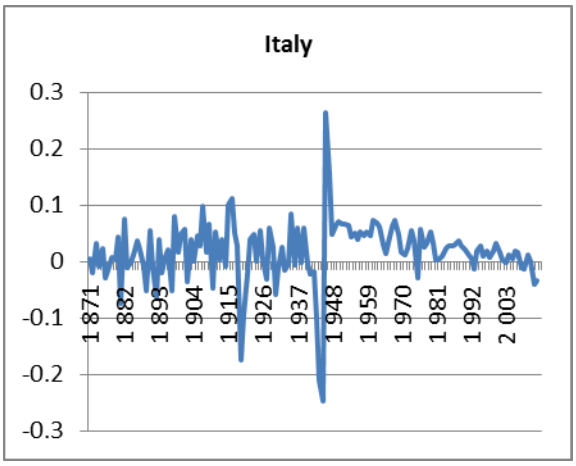


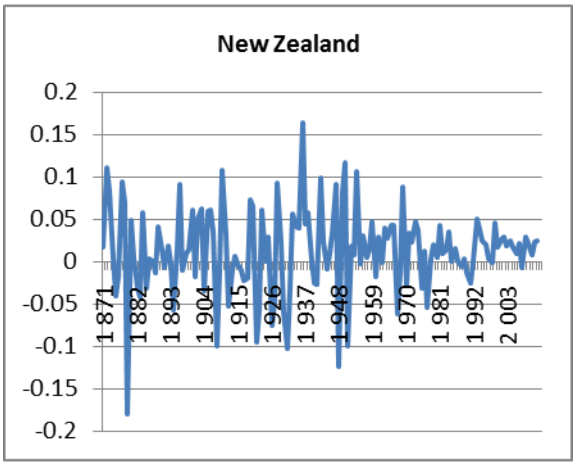

France
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

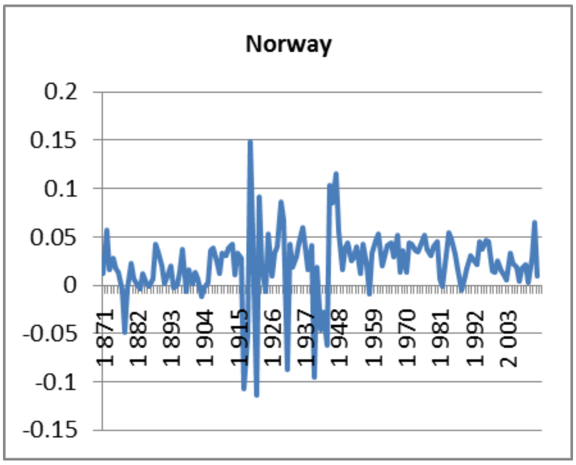

Japan
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

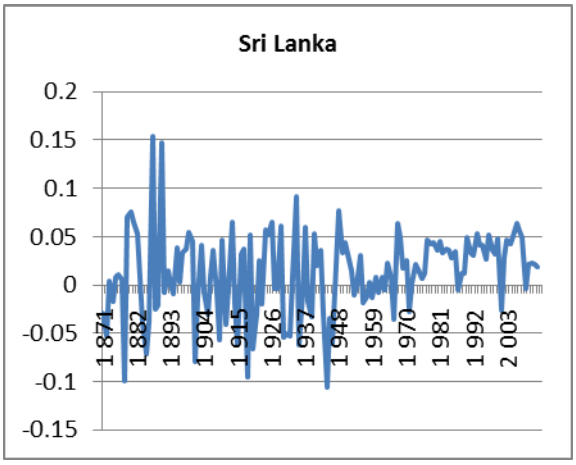

Germany
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

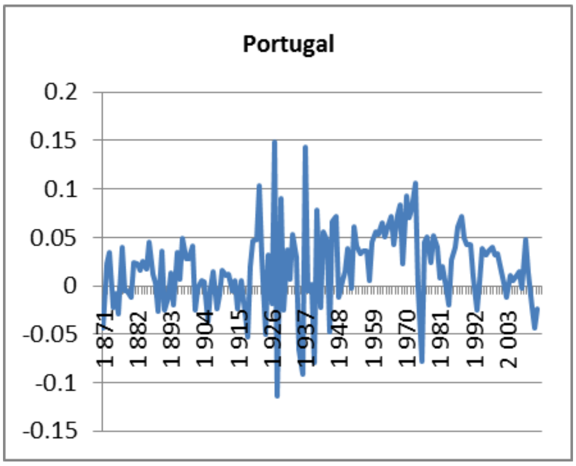

Netherlands
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

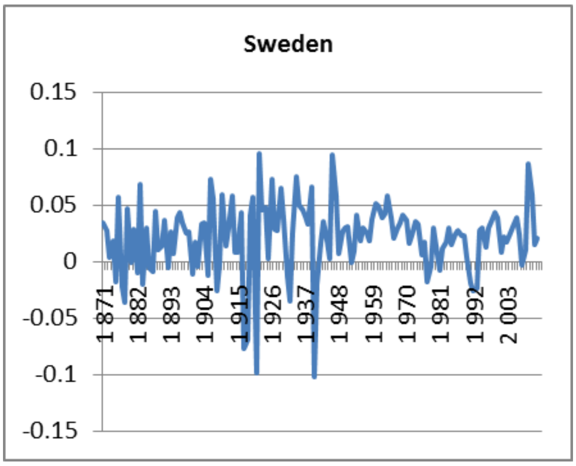

Italy
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

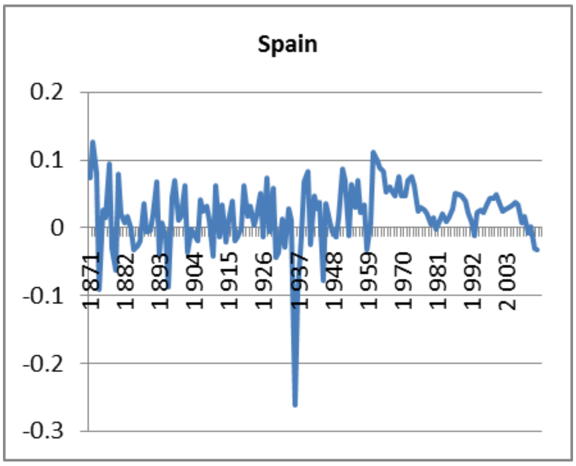

New Zealand
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

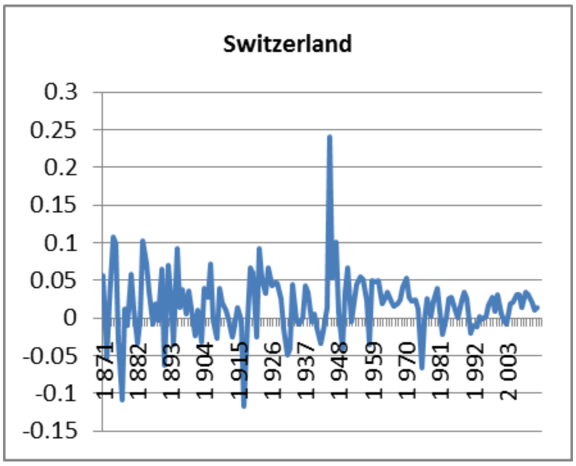

Norway
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

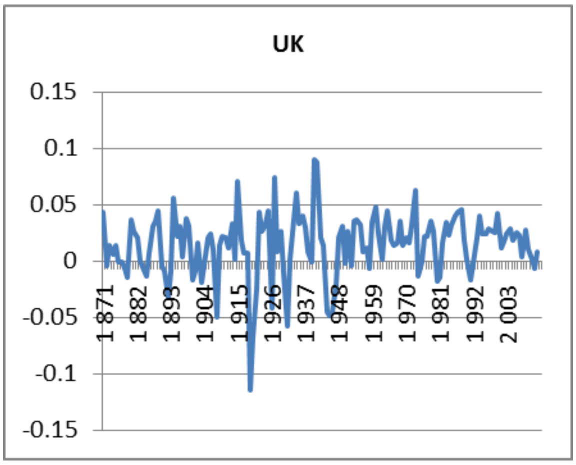

Sri Lanka
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

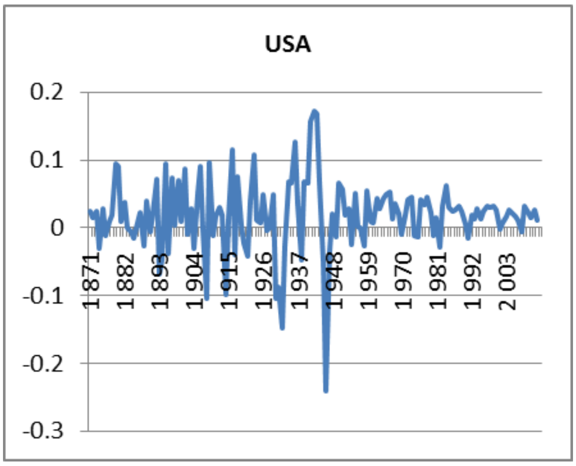

Portugal
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


Sweden
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


Spain
0.2
0.1
0
-0.1
-0.2
-0.3
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


Switzerland
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


UK
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


USA
0.2
0.1
0
-0.1
-0.2
-0.3
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

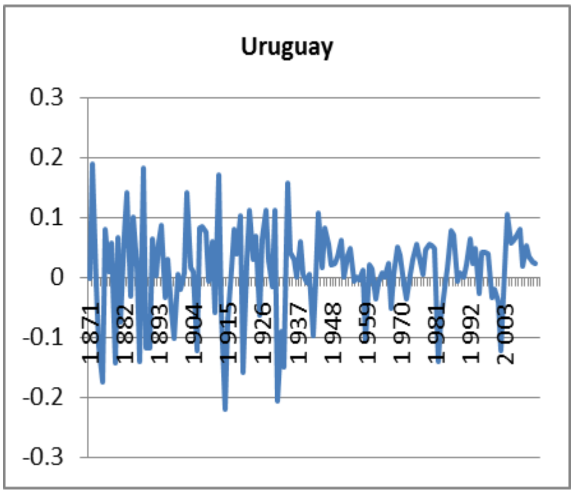
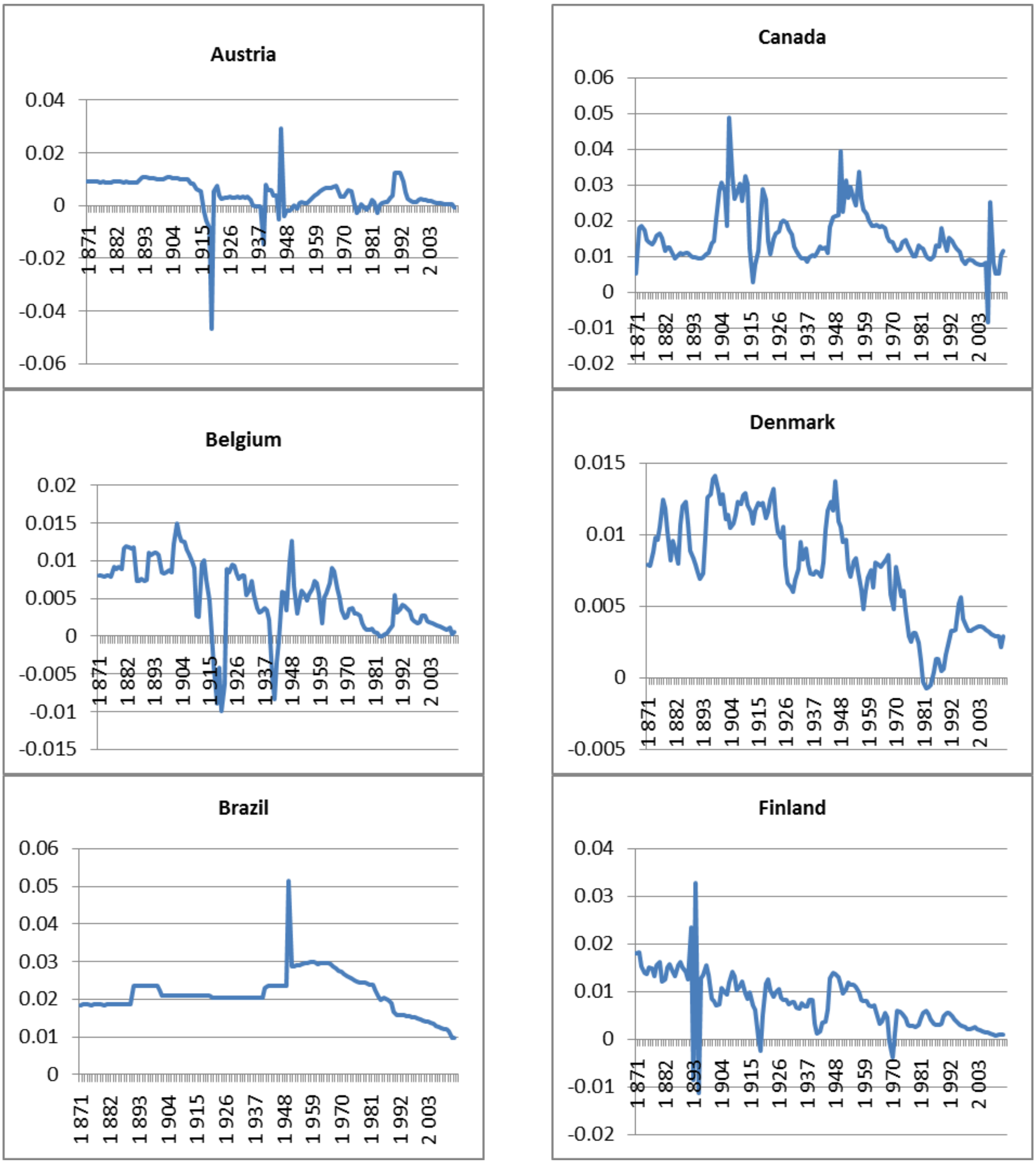
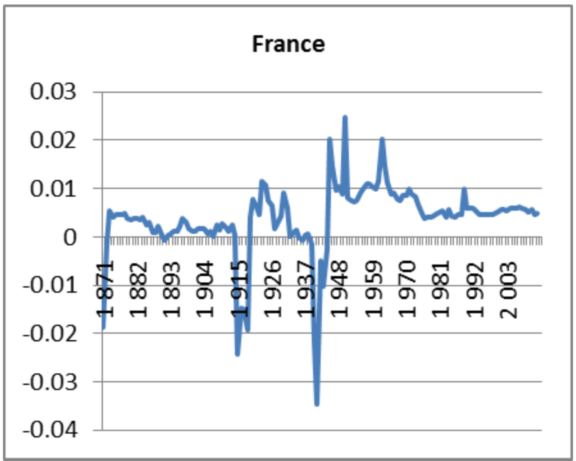
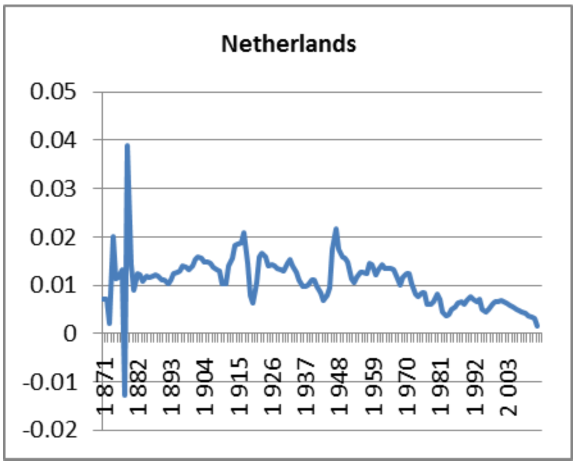
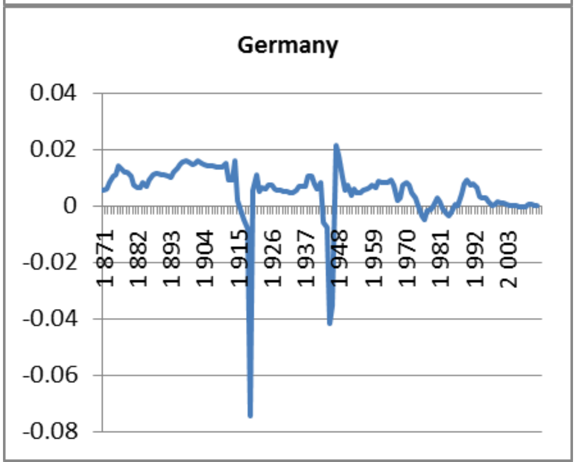

Uruguay
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

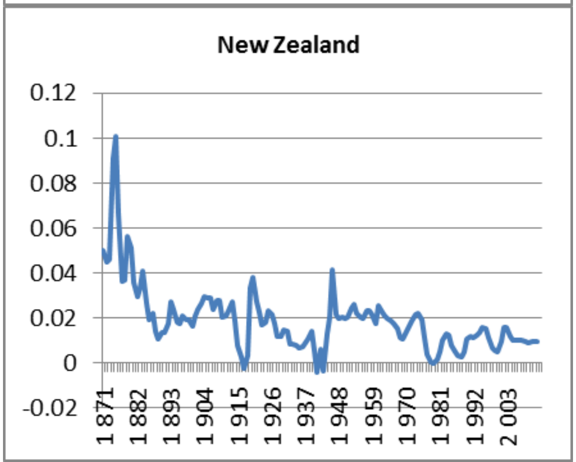
Figure 2: Plots of Population Growth Rates

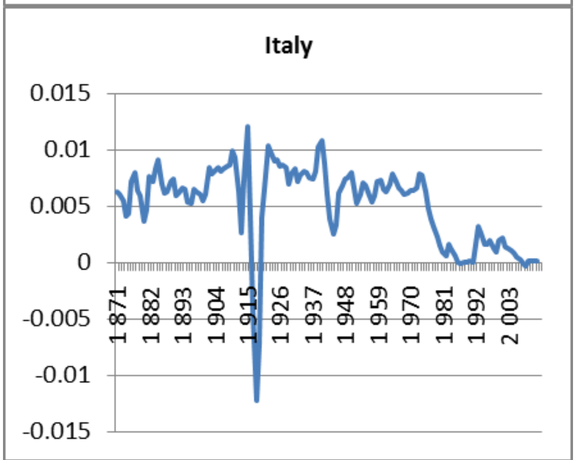


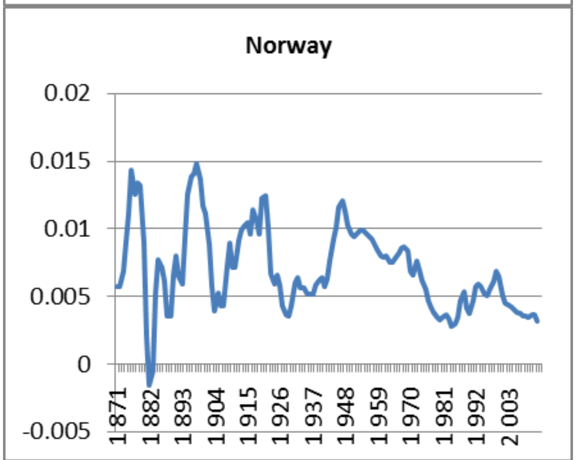

France
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

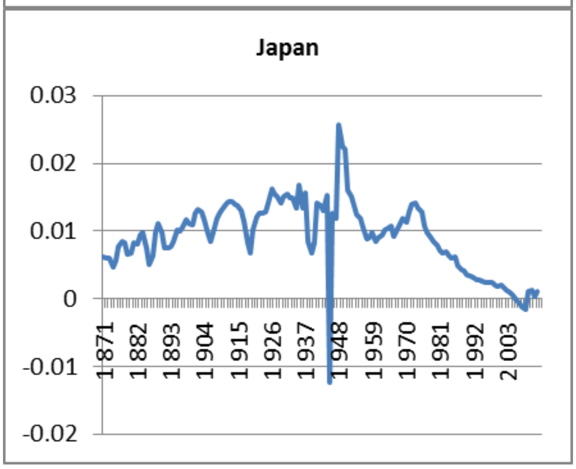

Netherlands
0.05
0.04
0.03
0.02
0.01
0
-0.01
-0.02
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

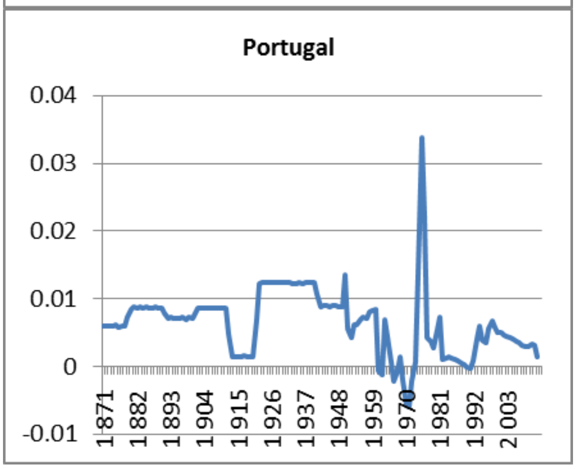

Germany
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003

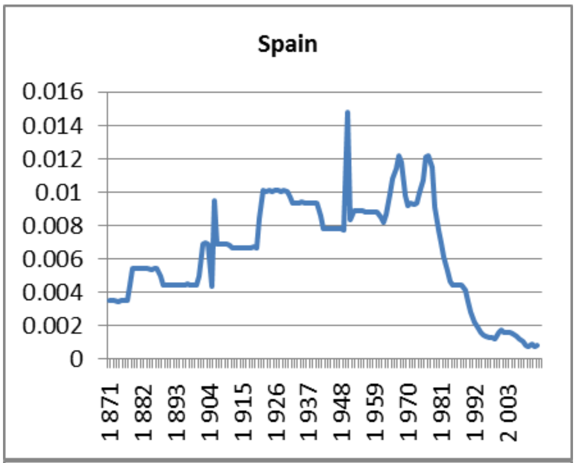

New Zealand
0.12
0.1
0.08
0.06
0.04
0.02
0
-0.02
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


Italy
0.015
0.01
0.005
0
-0.005
-0.01
-0.015
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


Norway
0.02
0.015
0.01
0.005
0
-0.005
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


Japan
0.03
0.02
0.01
0
-0.01
-0.02
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


Portugal
0.04
0.03
0.02
0.01
0
-0.01
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


Spain
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
1 871
1 882
1 893
1 904
1 915
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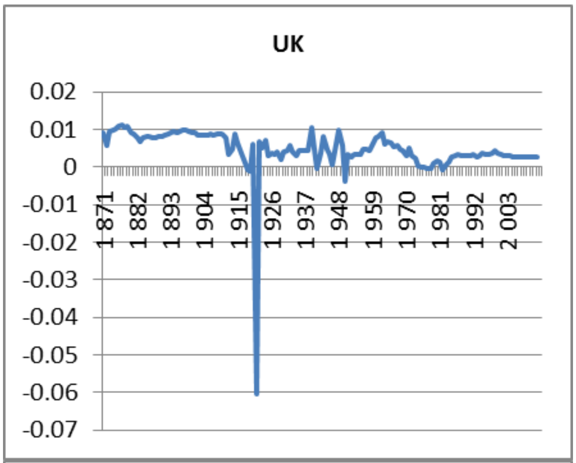
1 970
1 981
1 992
2 003


UK
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
-0.05
-0.06
-0.07
1 871
1 882
1 893
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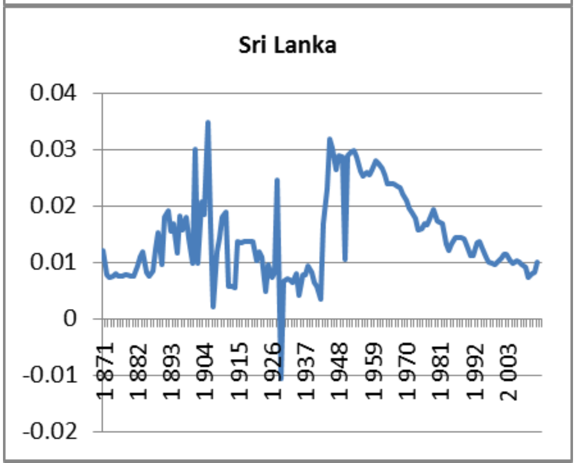
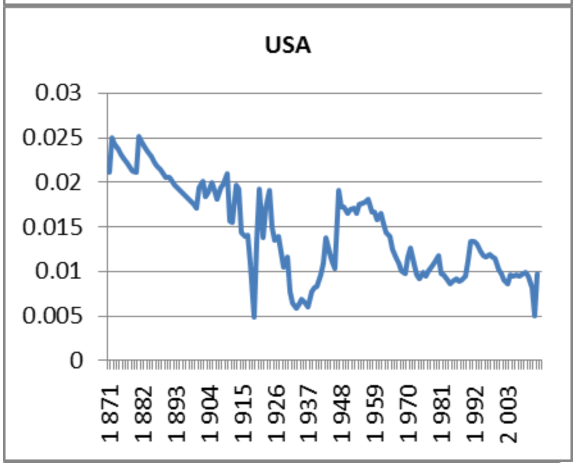
2 003


Sri Lanka
0.04
0.03
0.02
0.01
0
-0.01
-0.02
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


USA
0.03
0.025
0.02
0.015
0.01
0.005
0
1 871
1 882
1 893
1 904
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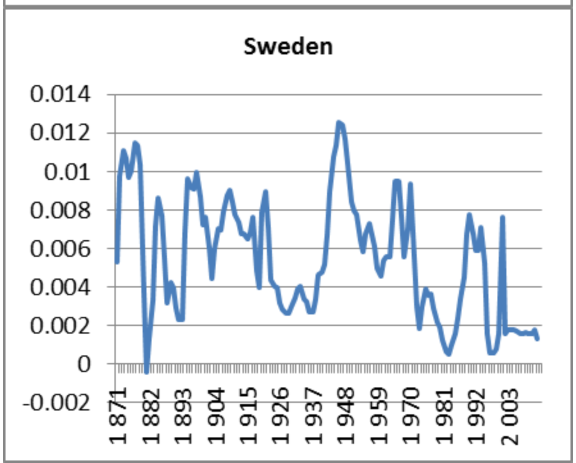
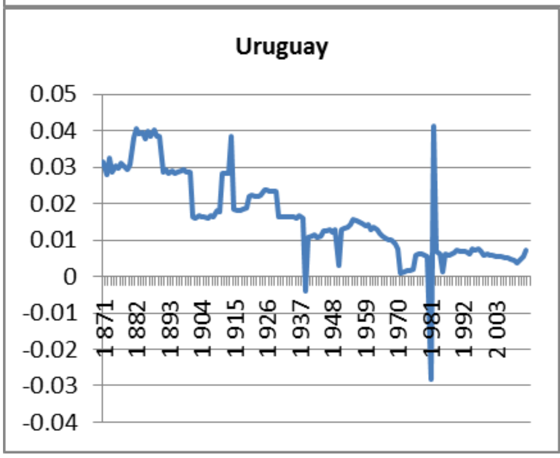
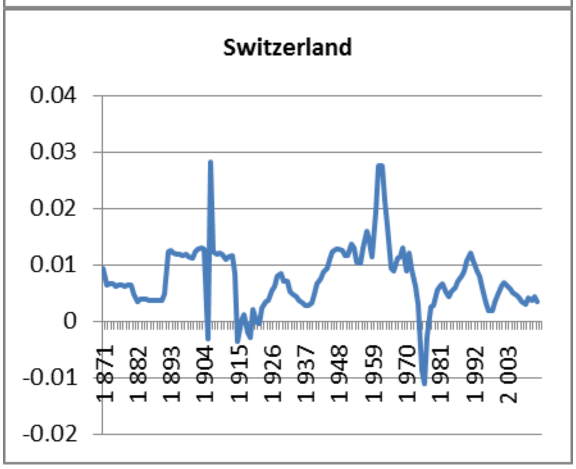
1 959
1 970
1 981
1 992
2 003


Sweden
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
-0.002
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


Uruguay
0.05
0.04
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003


Switzerland
0.04
0.03
0.02
0.01
0
-0.01
-0.02
1 871
1 882
1 893
1 904
1 915
1 926
1 937
1 948
1 959
1 970
1 981
1 992
2 003