CAUSATION BETWEEN HEALTH AND INCOME: A NEED TO PANIC

ABSTRACT

This paper tests whether health has improved or income has improved health in OECD countries over the last fifty years. A theoretical framework for both directions of causation is first outlined. A panel time-series approach is then taken and, unlike similar work, common shocks across countries ('cross-sectional dependence') are taken into account in the analysis using the PANIC approach of Bai and Ng. It is found that better health improves income more generally while income in turn also affects health. This finding is shown to be robust to dynamic specification and many mortality-based measures of population health.

KEYWORDS : causation, health ,income, cross-sectional dependence

1. INTRODUCTION

Pritchett and Summers (1996) baldly expressed the traditional economic view of the association between health and income: “Wealthier nations are healthier nations”. In their paper, they decided that the associative relationship between income and health was causal and structural through increased income buying greater quantities of health-enhancing public and private goods. The theoretical framework for this argument had been provided by Grossman (1972) who saw health as a form of capital stock to which consumers add investments. At the individual level, higher income allows the purchase of the inputs to good health e.g. nutrition, medicines and healthcare (Schultz 1999; Paxson and Schady, 2007) or through its association with better education encourages health-promoting lifestyle and behavioural choices (Feinstein, 1993). At the national level, more developed countries can expand public goods and services (Anand and Ravallion, 1993). A literature has developed on this basis examining income elasticities to determine whether health is a luxury good or a necessity (e.g. Newhouse, 1977 ; Gerdtham and Löthgren, 2000; Hall and Jones, 2007; Costa-Font et al., 2011).

An alternative view is that health as a measure of human capital is integral to the process of economic growth. The assertion that health could have a significant effect on income levels was first popularised by Jeffrey Sachs and the Commission on Macroeconomics and Health (WHO, 2001). They claimed that

> “… causal linkages running from health to development are extremely powerful, indeed much more powerful than has often been recognized by scholars and policy-makers. These linkages underpin the economic case for greatly increased investments in health….”

Studies find these impacts to be considerable: a permanent increment of 0.8 – 1.5% of annual income due to typical health improvements for Latin American countries (Mayer, 2001). A number of plausible mechanisms whereby health could influence income have been put forward. In addition to using up scarce resources in treatment, ill health reduces the supply of labour through reduced work effort, absenteeism and disability (Deolalikar 1988; Haas and Brownlie 2001, Murray and Lopez 1997a,b) and reduces human capital by impairing learning and discouraging parents from investing in their children's education (Ehrlich and Lui, 1991; Kalemli-Ozcan, 2002; Miguel and Kremer, 2004; Soares, 2005; Bleakley, 2007). Health also affects savings and investment decisions. Longer life spans with fixed retirement ages and prefunded pension systems necessitate increased savings (Lee et al 2000; Bloom et al. 2007; Lorentzen et al., 2008) while areas with a high disease burden are not attractive to capital investment (WHO, 2001). Empirical studies of economic growth which control for other aspects of human capital have found a positive and sizable effect of health on aggregate output (Bloom et al., 2004; Jamison et al., 2005). [1]

These opposing views are reconciled in a view of mutually-enforcing improvements: better health promotes economic growth which in turn allows the purchase of better health and development through a virtuous cycle of dynamic change (Bloom and Canning, 2000). In this paper I attempt to throw some light on the validity of this claim using recently developed econometric techniques for panel time series. In order to examine the dynamic interaction of income and health, I explore the time series properties of panels of OECD income and health data testing for cointegration and causation thus obviating the assumption of instantaneous relationships criticised by Bloom, Canning and Fink (2009). Tests for non-stationarity

[1] Weil (2007) finds a less substantial effect though he concedes that he did not consider the effect of health on the accumulation of physical and human capital

and cointegration are complicated by the potential for cross-sectional dependence (CSD) where shocks at a particular time to income or health across countries are potentially correlated. Common shocks to income across countries which are integrated economically would be expected such as an oil price shock which lowers aggregate output at the same time in similarly developed countries. Simultaneous positive shocks to health through procedural or technological advancement or common negative shocks to health such as new diseases (e.g. AIDS) also appear plausible. Leon (2011) notes the remarkable similarity in trends in life expectancy in European countries which he attributes to similarities in personal behaviours as well as diffusion of public health knowledge and medical treatments. Andrews (2005) concludes that this type of cross-section dependence is a common feature of economic data where shocks can be due to macroeconomic, technological, legal/institutional, political, environmental, health or sociological changes. Times series analysis has developed rapidly in recent years and results may well be nullified by failure to account for cross-sectional dependence (CSD). With that in mind, analysis here is confined to OECD countries where socioeconomic data may reasonably be expected to suffer from CSD. It is found that health as measured by life expectancy and GDP per capita are non-stationary and cointegration is found using the Bai et al. (2009) procedure to jointly estimate slope parameters and stochastic trends. The assumptions underlying this model are not found to be unnecessarily restrictive in this application. We then find as before that causation works in both directions and this result is robust to dynamic specification. As Bonds et al. (2009) note “the literature on the interactions between income and disease tends to be unidirectional and to focus on either the effects of (i) income on health or (ii) health on income”. The analysis carried out in this paper reflects the idea that there is a dynamic relationship between the two.

This paper is different to the current literature in a number of respects. Roberts (1999) and Gerdtham and Lothgren (2000) discuss the determinants of health care spending and use a cointegration analysis approach. They are principally motivated to carry out their studies by the identification of the determinants of health care spending and there is no suggestion in the two papers cited that health care expenditure causes GDP and as a result this type of analysis is not undertaken. A number of other papers do examine this direction of causation (Devlin and Hansen 2001; Erdil and Yetkiner 2009) but (i) they do not provide a theoretical framework for causation in both directions (ii) they use a VAR in differences to test for causation which is a misspecification if variables are non-stationary and cointegrated (as is generally found to be the case in the literature e.g. Freeman, 2003; Westerlund, 2007; Moscone and Tosetti, 2010) [2] (iii) they equate health care with health although medical care is only one of many inputs to the production of health and maybe not even the most important (Wagstaff, 1986 ; Evans and Stoddart, 1990). Grossman (1999) also notes healthcare expenditure and health outcomes are not the same: the model he describes "..emphasizes the difference between health as an output and medical care as one of many inputs into the production of health".

The other contribution of this study is the application of recently developed second generation approaches to testing for cointegration and causation. First generation approaches to panel unit root and cointegration testing assume independence across the different units in the panel. These tests are invalidated when the units are contemporaneously correlated and this is often the case in empirical

[2] See Hamilton (1994) for the econometric argument

applications. This is discussed later in section 3 in more depth. Estimation of the cointegrating relationships is also often confounded by unobserved common factors. Andrews (2005) and Bai et al. (2009) show how common shocks can invalidate estimation and inference of cointegrating parameters. The literature on modelling of cross section dependence has developed rapidly over the last decade and an excellent review is available from Breitung and Pesaran (2008).

Unlike Baltagi and Moscone (2010) we do not consider spatial dependence across countries here. They acknowledge that the medical literature justifying this approach is concerned with localized variations and, in our opinion, the justification for dependencies across national boundaries appears weak. However, we may examine spatial dependence in future work.

The remainder of this paper is organized as follows. Section 2 outlines the theoretical justification for cointegration between health and income while the data and econometric methodology are described in Section 3. In section 4 we present our results and in the final section we discuss their implications.

2. THEORY

In this section theoretical arguments for both (i) health improving income (section 2.1) and (ii) income improving health (section 2.2) are presented. This provides a motivation for testing both directions of causation in the analysis.

2.1 Goods production

Looking at goods production, we follow Barro (1996) and describe the production process by a Cobb-Douglas expression so as to simplify matters :

$$Y = AK^{\alpha}S^{\beta}H^{\gamma}\left(Le^{xt}\right)^{1-\alpha-\beta-\gamma} \tag{1}$$

where $\alpha > 0$, $\beta > 0$, $\gamma > 0$ and $0 < \alpha + \beta + \gamma < 1$. Output Y is produced by combining physical capital K, with human capital in the form of schooling S and health capital H and with labour L. Technological improvement occurs exogenously at rate x from a baseline A. The presence of health capital in this formulation follows from arguments given above on health improving effort, increasing the size of the disability-free labour force and enhancing the effectiveness of schooling. We then have output per unit of effective labour is

$$\hat{y} = A\hat{k}^{\alpha}\hat{s}^{\beta}\hat{h}^{\gamma} \tag{2}$$

where $\hat{y} \equiv Y/Le^{xt}$, $\hat{k} \equiv K/Le^{xt}$, $\hat{s} \equiv S/Le^{xt}$, $\hat{h} \equiv H/Le^{xt}$.

This output is then consumed or reinvested by the household in each of the forms of capital and capital stocks accumulate as follows where a dot above a variable indicates the derivative with respect to time:

$$\begin{aligned} \hat{y} &= \hat{c} + \hat{i}_k + \hat{i}_s + \hat{i}_h \\ \dot{\hat{k}} &= \hat{i}_k - (\delta + x + n)\hat{k} \\ \dot{\hat{s}} &= \hat{i}_s - (\delta + x + n)\hat{s} \\ \dot{\hat{h}} &= \hat{i}_h - (\delta + x + n)\hat{h} \end{aligned} \tag{3}$$

where $\hat{c}$ is consumption per unit of effective labour; $\hat{i}_k$, $\hat{i}_s$ and $\hat{i}_h$ are investment per unit of effective labour in physical, schooling and health capital respectively; δ is the rate of depreciation for both physical and human capital and n is the exogenous and constant rate of population growth. For reasons of tractability, a common depreciation rate for physical and human capital is often assumed (e.g. Barro and Sala-i-Martin, 2004 ; Mankiw, Romer and Weil, 1992). Different depreciation rates would complicate the algebra without providing much additional insight.

For all three forms of investments to occur, the rates of return must be equated across all three types of capital.

$$\begin{aligned} &\alpha A\hat{k}^{\alpha-1}\hat{s}^{\beta}\hat{h}^{\gamma} - \delta = \beta A\hat{k}^{\alpha}\hat{s}^{\beta-1}\hat{h}^{\gamma} - \delta = \gamma A\hat{k}^{\alpha}\hat{s}^{\beta}\hat{h}^{\gamma-1} - \delta \\ &\Rightarrow \hat{s} = \left(\frac{\beta}{\gamma}\right)\hat{h} \text{ and } \hat{k} = \left(\frac{\alpha}{\beta}\right)\hat{s} = \left(\frac{\alpha}{\gamma}\right)\hat{h} \end{aligned} \tag{4}$$

where $s = S/L$ and $h = H/L$. The literature reviewed in the introduction gives plausible explanations for why schooling and physical capital might be a function of health and it is therefore a reasonable next step to use the formulations in (4) with health as the main driver.

We express the levels of each capital stock as a ratio of the level of health stock. Substituting (4) in (2) and taking logs,

$$\log \hat{y} = \left(\log A + \alpha \log \frac{\alpha}{\gamma} + \beta \log \frac{\beta}{\gamma} \right) + \left(\alpha + \beta + \gamma \right) \log \hat{h} \tag{5}$$

Or more simply and in per capita terms,

$$\log y = \alpha' + \beta' \log h \tag{6}$$

where $y = Y/L$, $h = H/L$, $\alpha' = \left(\log A + \alpha \log \frac{\alpha}{\gamma} + \beta \log \frac{\beta}{\gamma} \right)$ and $\beta' = \left(\alpha + \beta + \gamma \right)$.

Therefore health status directly affects the level of (real) income per capita. Real GDP per capita is used to measure y . As longevity correlates closely with good health (UNHDP,1990; WHO, 2000) we use life expectancy to proxy for h . [3]

2.2 Health production

We now turn our attention to the production of health. We can consider health as a private good partially financed by government. Modifying the mechanism for the evolution of health capital stocks in (3), we have:

$$\dot{\hat{h}} = (\hat{e}_h + \hat{i}_h) - \left(\delta + x + n \right) \hat{h} \tag{7}$$

where $\hat{e}_h$ is health-promoting government expenditure per unit of effective labour which includes healthcare, health promotion, housing, education and sanitation. As in Barro (1996) or Chakraborty (2004), this is financed by a proportional tax at rate τ on income

$$\hat{e}_h = \tau \hat{y} \tag{8}$$

Private health-promoting spending including nutrition, physical activity and medical expenses is assumed here to be a constant proportion of income and hence the private contribution to health capital stocks, $\hat{i}_h$, is

$$\hat{i}_h = \eta \hat{y} \tag{9}$$

for some fixed η . Greater income also allows more tobacco, alcohol and fat to be consumed and hence $\hat{i}_h$ represents a net investment in health due to private spending. Substituting (9) and (10) in (8) we then have

[3] No population health measure is perfect. Murray et al. (2000) discuss a number of basic criteria important in summary measures of health and conclude that no standard measure satisfies all.

$$\dot{\hat{h}} = (\tau+\eta)\hat{y} - (\delta + x + n)\hat{h}$$

and in the long-run, $\dot{\hat{h}} = 0$. Hence

$$\hat{h} = \frac{(\tau+\eta)}{(\delta+x+n)}\hat{y} \tag{10}$$

In per capita terms and using life expectancy[4] again to proxy for h,

$$\log h = \log\frac{(\tau+\eta)}{(\delta+x+n)} + \log y \tag{11}$$

The theoretical justification for a cointegrating relationship between health and income is then given by (7) where changes in health status are driven by income variations or (11) where average income determines health. In the event that we find statistical evidence for cointegration between GDP per capita and life expectancy either one or maybe both of these mechanisms are feasible.

I follow a specific-to-general approach where the analysis concentrates on a small set of variables of core interest (health status and income). This is the leading approach in applied systems cointegration analysis (Lutkepohl, 2007). I do not attempt to model an entire system describing the data generating processes for health status and income with a large number of plausible factors for several reasons. In the absence of the simplifying assumptions, there are obvious data limitations in trying to estimate the parameters in a system including all relationships considered in the theoretical section. Gonzalo and Pitarakis (1999) also argue that system cointegration tests have poor small sample properties in large dimensional systems. Hence, an approach based on first identifying cointegrating relations among subsystems of smaller numbers of variables is better able to identify any important relationships. Furthermore, if a set of variables is found to be cointegrated, adding further variables to the system does not change the conclusion that the original variables are cointegrated. It may simply lead to the finding of further cointegrating relationships.

[4] Life expectancy is also determined by the demographic structure of the population but this is presumed to be stable over the period considered.

3. DATA AND METHODOLOGY

3.1 Data

The focus in this paper is on developed economies for the following reasons. In order to exploit the power of panel approaches it was decided to select countries where the relationship between health- income relationship might be similar. Contemporaneous shocks to disease or healthcare technologies are unlikely to be common to both developing and developed countries. Also many less developed countries lack complete vital registration systems and life expectancy, used here as a proxy for health, is often estimated through sampling techniques or imputation based on out-of-date information (Bos et al., 1992). Furthermore, it is perhaps a more interesting result to find that economic growth is dynamically related to health in the OECD countries studied here than in the developing country context emphasised by the Commission on Macroeconomics and Health.

Complete annual data on life expectancy at birth for the total population was available from the World Development Indicators 2009 (World Bank) for only sixteen of the thirty OECD countries for the period 1960-2007. Real gross domestic product per capita in 2005 constant prices (Laspeyres) from the Penn World Tables Version 6.3 (Heston et al., 2009) was sourced for the same years and a further three countries (all former Eastern bloc) were dropped leaving thirteen countries in all. [5] Only original data was used and no interpolation was carried out. [6]

OECD Health Statistics allowed the use of a number of alternative mortality - based health status measures to be used in order to assess the robustness of results.

[5] Austria, Denmark, Finland, France, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden Switzerland, and United States

[6] Alternative data sets such as OECD Health data are similarly incomplete. In OECD Health Data 2011, life expectancy at birth for the total population is only available from 1960 for 18 countries and GDP per capita in real terms is only available from 1960 for four countries.

When life expectancies at birth and at age 60 by gender for 1960-2007 were combined with real GDP per capita data, a dataset of time series for thirteen different countries to those above was formed.[7] Infant mortality data was more complete and when combined with GDP data, a dataset of twenty-four countries was formed.

3.2 Methodology

Contemporaneous error correlation is often observed in empirical economics due to omitted common factors or unobserved common factors. Standard panel unit roots tests and tests for cointegration rely on the assumption of zero contemporaneous error covariance across countries in order that the statistical properties can be easily derived. These 'first generation' tests where cross-sectional error independence is assumed have been supplanted by recently developed second-generation tests and are described in more detail below.

CSD might be expected in income data among countries economically linked as their business cycles will be closely aligned and technological innovations will be rapidly diffused. Health status measures may also be correlated across countries as medical technology, medical practices and public health interventions are diffused. This is discussed more fully in section 4.

Cross sectional dependence

We first of all check if CSD is a problem in our analysis. Pesaran (2004) has developed a test for error cross–sectional dependence applicable to unit root dynamic heterogeneous panels given by

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

[7] Australia, Austria, Belgium, France, Japan, Mexico, Netherlands, Norway, Portugal, Sweden, Switzerland, Turkey and United States

for a panel of N countries and length T where $\hat{\rho}_{ij}$ is an estimate of the cross-sectional error correlation. This is asymptotically standard normal under the null hypothesis of independent errors for individual OLS estimates. Although positive and negative error correlations $\hat{\rho}_{ij}$ may combine to produce a Type I error, rejection of the null hypothesis (as I find later) should provide convincing evidence of CSD.

Unit roots

The "first-generation" panel unit root tests (e.g. Levin and Lin, 1993; Im, Pesaran and Shin, 2002 (hereafter IPS); Hadri, 2000) assume that shocks, u_{it} ,to individual processes, $\Delta Y_{it} = \alpha_i + \varphi Y_{it-1} + u_{it}$, are identically independently distributed across i and t allowing the construction of combined normally distributed statistics. O'Connell (1998) argued that CSD resulting in oversized tests on the one hand and on the other hand a lack of power even when corrected critical values were used (also Phillips and Sul, 2003). Banerjee *et al.* (2005) show that many of the standard panel unit root tests are over-sized in the presence of cross-unit cointegration. Remedies for the problem of CSD in panel unit root testing include the PANIC (Panel Analysis of Nonstationarity in Idiosyncratic and Common components) methodology developed by Bai and Ng (2004). This involves separating nonstationarity into that part that is pervasive cross individuals and that part that is idiosyncratic to a particular individual. They then test both parts independently for non-stationarity. The number of common factors, r, can be determined by applying the criteria based on principal components outlined in Bai and Ng (2002). Tests with the null of stationarity are less common with Hadri and Korizumi (2008) extending the standard Hadri panel test using a single common factor set-up. In contrast to the Bai and Ng procedure, the common factor is treated here as a nuisance and eliminated. In a Monte Carlo simulation study of panel unit root tests accounting for CSD, Gengenbach, Palm and Urbain (2010) concluded that the Bai and Ng test was the only one to allow for non-stationarity due to common factors.

Cointegration tests

First generation cointegration tests (Kao, 1999; Pedroni, 2004) are also adversely affected by CSD with test statistics shown to be no longer asymptotically normal (Gengenbach et al., 2006). Banerjee et al. (2004) find Pedroni cointegration tests are oversized in the presence of cross-unit cointegration.

As a development of their PANIC methodology, Bai et. al. (2009) suggested a continuous updated bias-corrected (*Cup BC*) estimator and a continuous updated fully-modified (*CupFM*) estimator to estimate δ in $y_{it} = x_{it}^{'}\delta + \mathbf{f}_t^{'}\pi_i + \varepsilon_{it}$ where

- x_{it} is I(1)
- $\mathbf{f_t}$ is I(1) or I(0) and potentially correlated with x_{it}
- ε_{it} is I(0) but cross-sectionally independent.

Bai and Ng (2008) suggest using the *CupBC* and *CupFM* estimators to estimate the cointegrating relationship and then test the residuals for stationarity. Pooled test statistics are then constructed based on standardisation. In the event that cointegration is found a Granger causality testing approach is then pursued.

4. RESULTS

Data from the beginning and end of the time series is given in Table 1. Over this period countries have enjoyed spectacular increases in life expectancy and income. In the most extreme case, Japan extended life expectancy by almost a quarter (22%) and increased income by over four times in real terms (457% increase). Countries with low economic growth generally did not show significant health improvements and vice versa. Sweden and the Netherlands, for example, both rank among the lowest in improvements for both variables (11^{th} and 10^{th} respectively in percentage income growth and 10^{th} and 11^{th} in percentage life expectancy increase). When life expectancy and GDP per capita are expressed in logarithmic terms as in the equations (7) or (11) above we see convergence with the standard deviations in both variables reducing over time (0.028 to 0.016 for life expectancy and 0.335 to 0.169 for log GDP per capita).

I next test for the prevalence of CSD in this data. Table 2 gives the average absolute cross-section correlation for the observed values, for the errors from individual autoregressions (second row) and for individual OLS on the two variables (third row). Running autoregressions for each individual country separately with a constant and time trend we can see that the residuals are correlated with average absolute cross-sectional correlation of 0.320 for Log GDP per capita ('GDP') and 0.257 for log life expectancy ('LE'). This invalidates the standard panel unit root tests[8]. Any of the first-generation cointegration tests are also seen to be invalidated from the high level of correlation in the individual country OLS residuals (0.498 when income is the dependent variable and 0.507 when life expectancy is dependent). More formally, the p-value for the standard normally distributed CD-statistic in (1) for testing CSD in residuals is given in parentheses. The null of independent errors is convincingly rejected in the autoregressions (CD=18.7 for income and CD=14.6 for life expectancy) and also in the cross-sectional regressions (CD=30.2 when income is the dependent variable and CD=30.8 when life expectancy is dependent). CSD in innovations in European GDP per capita was also found in Pesaran (2004). In

[8] Without trend , the null of independence was still convincingly rejected

particular UK output innovations were dependent on innovations in output of countries in Europe, USA/Canada and Asia/Australia in that order. Short-run fluctuations in output would be expected to be correlated in countries exposed to each others' economies through trade. Technology diffusion from leader countries to followers through imitation and implementation of discoveries would also cause correlated increases in output. Cross-country correlations in changes in life expectancy are not unexpected either as Cutler et al. (2006) found a simultaneous decline in mortality rates in developed countries due to the diffusion of medical technology and contemporaneous changes in mortality risk factors. Improved neonatal medical care for low birth-weight infants has lead to infant mortality reductions while reductions in smoking which causes cardiovascular disease and lung cancer has been simultaneously declining in developed countries. Soares (2005) also notes the importance of cross-country technology diffusion in mortality reduction through the transfer of knowledge about public practices and personal health behaviour.

TABLE 2 HERE

The first step in the application of the Bai and Ng test is the determination of r, the number of factors. A number of criteria are outlined in Bai and Ng (2002) which treat the addition of extra factors to the model as a classical model selection problem. However, these criteria were developed for large panels and are inadequate when $\min\{N,T\} < 40$. With an OECD panel of larger T than used here, Choi and Chue (2007) report the number of factors chosen always tends to equal the maximum number pre-selected in the routine and this is also what I found in my work. Therefore in this paper I follow Bai and Ng (2001) where in their empirical application the authors forego the panel criteria in favour of one factor due to small N [9].

TABLE 3 HERE

Applying the Bai and Ng test, I find that the first principal component explains 42% and 37% of the variation in the first-differenced GDP and Life Expectancy panels respectively confirming the importance of common factors seen in the first row of Table 2. The strength of the common trend in life expectancy is surprising and the relative contributions of medical technology diffusion and concurrent changes in lifestyles to this factor are not clear. Testing the series for unit roots we see from the second row in Table 3 that the null of non-stationary idiosyncratic components is accepted in all cases inducing non-stationarity in both variables. Also the common factors generally appear to have unit roots except in the specification for GDP which includes a time trend. Using first generation tests, non-stationary income per capita has been found in many papers (Westerlund, 2007; Levin, Lin and Chu, 2002; Gerdtham and Löthgren, 2000).

TABLE 4 HERE

Following Bai and Ng (2008) test for cointegration, the data is first–differenced and then the continuously-updated and bias-corrected (CupBC) and the continuously-updated and fully-modified (CupFM) estimators of Bai et al. (2009) are applied to account for potential correlation between the first-differenced explanatory variable

[9] N=21 in their analysis of Bureau of Labour Statistics price indices. See note 10 p15 Bai and Ng (2001).

and the first-differenced unexplained factor. A modified Sargan–Bhargava test as described in Bai and Ng (2008) is then applied to the residuals and pooled over countries (Table 4). The null of no cointegration is rejected indicating the importance of joint estimation of the unobserved factors and the slope parameters. It has been argued above that the common trend in income may be due to technology diffusion and that this should in turn also be correlated with trends in country-specific life expectancy does not seem unreasonable.

To test for causation an error-correction mechanism is estimated using the cointegrating relationship established above (Table 5). The coefficient on the error correction term ('gamma' term) is significant regardless of the specification of the dependent variable or the number of lags and is signed correctly. Economic growth theory would suggest that convergence to steady state values is very slow and adjustment in income of 12% each year to departures from its long-run relationship with life expectancy would seem relatively fast. The short–run parameters of the exogenous variable ('beta' terms) are also always significant and hence there is bidirectional causation. Pesaran and Smith (1995) highlight the potential to underestimate short-run parameters when parameter homogeneity is imposed in the presence of latent heterogeneity. Allowing short-run parameters to be hetergeneous will therefore not change conclusions here.

Given that life expectancy and income are logged, the long-run relationship estimate of $\hat{b} = 5.192$ indicates a positive and significant relationship between the variables with a 1% increase in life expectancy causing a 5.2% increase in GDP per capita. Positive, sizeable, and statistically significant effects of health on output of this order are reviewed in Bloom et. al.(2004). Their own estimate, which comes from an aggregate production function approach, is that a one-year increase in life expectancy raises output by 4 percent while the thirteen other studies reviewed have similar quantitative results.[10] Total factor productivity is captured in their model as here (see (2)) by fixed effects and parameter values are otherwise assumed to be constant across countries. The effect of income on health is also positive and significant but very small with a 1% increase in income per capita only causing a 0.02% increase in life expectancy which for the UK in 2007 would be 0.01 years. Other studies of developed countries have found the effect of income on life expectancy at birth controlling for health care expenditures, behaviours and environment to be insignificant (Auster et al., 1969 ; Miller and Frech, 2000; Thornton 2002) while Fayissa et al. (2005) find a 1% GDP increase improves life expectancy by between 0.05% and 0.14% in sub-Saharan countries. The size of the effect found here indicates that any beneficial improvements in health caused by extra income mediated through greater consumption of health care inputs are largely offset by increases in mortality associated with unhealthy changes in lifestyles and behaviours and perhaps the negative environmental health effects of upturns in the business cycle as suggested by Ruhm (2004).

TABLE 5 HERE

To test the robustness of results, the analysis is repeated for a number of alternative mortality-based measures of health status taken from OECD Health Statistics. In the first instance, the analysis above is repeated for life expectancy for the total population from this dataset and then results are given by gender and for infant/ older

[10] Though more recent results are more modest, see Weil (2007). Some authors have also argued that there should be no positive effect. As health interventions have the largest effect on infant mortality, a reduction in the disease burden may lead to an increase in national income but this becomes a deterioration in income per capita once the positive effect on population is included (Acemoglu and Johnson, 2007 ; Ashraf et al. 2009).

age mortality. In this case the countries considered also include two less developed OECD countries: Turkey and Mexico. Results are given in Table 6. All variables are non-stationary (rows 4-7). For the life expectancies, both the common factor and the idiosyncratic parts are unit roots while for infant mortality only the idiosyncratic part is non-stationary when a constant is included in the specification. For the specification including constant and trend, both parts of the infant mortality data are nonstationary. It is clear that infant mortality is not cointegrated with income. This is not surprising when spending on infant care has increased much more rapidly than the average cost of health services. In 1949 spending on low-birth weight babies was less than on normal weight babies as little could be done for them (Cutler and Meara, 2000). In this century, the spending ratio in developed countries is of the order of 10 to 20 times greater as better technology and treatments have become available. Conditional on birth weight, medical care is by far the most important factor in determining infant survival. Cointegration is found for all the other mortality measures but the null of no cointegration is rejected only at the 10% level for life expectancies at birth by gender. Estimation of the error correction mechanism gives similar results to before taking into account that standard errors will be larger when working with smaller sub-populations and a set of countries more diverse socioeconomically than in the previous analysis. For both directions of causation the dependent variable responds to departures from the long-run relationship ('gamma' term) with speeds of adjustment of similar magnitude to those given previously - comparing 13% - 22% in row 13 of Table 6 with 13% in row 7 column 5 in Table 5 and 16%-23% in row 20 of Table 6 with 19% in row 7 column 3 in Table 5 . For all mortality measures, the dependent variable also responds to the short-run parameters hence the previous finding of bidirectional causation holds. Estimates of parameters in the long relationship (the ‘b’ term) are slightly lower than previously but generally consistent across sub-populations. The effect of old age mortality on income is lower with a 1% increase in life expectancy at age 60 for males and females causing a 1.3% and 1.4% increase respectively in income compared to 3.7% for the population as a whole. As the effect of health on income was posited to take place through its direct effects on the active labour force (see section 2.1), the effect of mortality among those already retired on the production of goods should be lower than for the general population. In the last two rows of the table, the effect of income on health becomes statistically insignificantly different to zero when analysing sub-populations. Mortality for smaller populations will be more subject to random variation and hence standard errors will be larger. However, parameter estimates are consistent ranging from 0.009 to 0.015.

In summary, we have seen health and income are cointegrated with bidirectional causation while taking account of cross-sectional dependence. An approach to examining the relationship between health and income using a time-series approach is useful as analyses based on the assumption that all countries are always at their steady state levels are misleading. However there are still timescale limitations to dynamic approaches as for example the length of current datasets do not permit analysis of lagged effects of health on income of the length suggested by Barker (1992) and Bleakley (2009) or the much longer term effect of historical mortality on the form of current institutions affecting the economy (Acemoglu et al. 2007) . Changes to both income and life expectancy in the first half of the twentieth century were much larger than in the time period considered here and data for that period would provide a more robust test of these results. This is a consideration for future work.

5. CONCLUSION

The analysis carried out in this paper uses the Bai and Ng PANIC methodology to deal with cross-sectional dependence. The result of cointegration reflects the idea that there is a dynamic relationship between health and income and bidirectional causation is observed. This provides support to the view of Bloom and Canning (2000) of virtuous spirals of mutually reinforcing health and economic improvements as has been observed in East Asia, Ireland and other wealthy industrial countries and vicious spirals of plummeting incomes and declining life expectancy as in Russia at the end of the twentieth century.

Mortality modelling in actuarial studies rely on factorial approaches similar to those considered here and an extension of this work will investigate socioeconomic determinants of mortality decline in the OECD. As acknowledged by many authors, health is multidimensional and there are many alternative measures of health status capturing morbidity, disease burden or self-reported health that could also be considered. An analysis by disease grouping (as in Adda et al. 2009) or by the different channels posited for effects on growth (as in Lorentzen et al. 2008) would also help deepen understanding of the processes at work.

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TABLES

Table 1. Summary statistics

	Life expectancy at birth		Real GDP per capita ($, 2005 prices)	
	1960	2007	1960	2007
Austria	68.6	80.0	$ 9,812	$ 36,027
Denmark	72.2	78.3	$ 11,120	$ 34,287
Finland	68.8	79.3	$ 8,696	$ 32,481
France	70.2	81.0	$ 9,385	$ 29,632
Italy	69.1	81.3	$ 8,240	$ 28,816
Japan	67.7	82.5	$ 5,493	$ 30,587
Netherlands	73.4	80.2	$ 11,961	$ 34,391
New Zealand	71.2	80.1	$ 12,394	$ 25,397
Norway	73.6	80.4	$ 11,715	$ 48,391
Spain	69.1	80.9	$ 5,879	$ 31,443
Sweden	73.0	80.9	$ 12,020	$ 32,952
Switzerland	71.3	81.7	$ 18,103	$ 37,309
United States	69.8	78.0	$ 14,737	$ 42,897

Table 2. Cross-sectional dependence statistics

	GDP	LE
$\lvert\hat{\rho}_u\rvert$	0.320 (CD=18.7, p=0.000)	0.257 (CD=14.6, p-value=0.000)
$\lvert\hat{\rho}_e\rvert$	0.498 (CD= 30.2, p=0.000)	0.507 (CD=30.8, p-value=0.000)

Note: $\lvert\hat{\rho}_u\rvert$ is the average absolute cross-section correlation of errors $\hat{u}_{it}$ in $X_{it} = \hat{\alpha}_{0i} + \hat{\alpha}_{1i}\,t + \hat{\alpha}_{2i}X_{it-1} + \hat{u}_{it}$

$\lvert\hat{\rho}_e\rvert$ is the average absolute cross-section correlation of errors $\hat{e}_{it}$ in $Y_{it} = \hat{\beta}_{0i} + \hat{\beta}_{1i}X_{it} + \hat{e}_{it}$

where column heading is Y and X is the neighbouring column heading

Pesaran's CD-statistic for testing the null hypothesis of independent errors is given in parentheses along with corresponding p-values.

Table 3. Bai and Ng (2004) test of non-stationarity

	GDP		Life expectancy	
	With constant only	With constant and linear trend	With constant only	With constant and linear trend
$ADF_{\hat{F}}$	-1.917	-3.453	0.106	-2.046
$P_{\hat{\varepsilon}}$	0.145	1.890	1.071	0.710

Note : Using model $X_{it} = c_i + \beta_i t + \lambda_i^{'} F_t + e_{it}$ we test for unit roots in F_t and e_{it} separately. Two lags are used.

If r=1, the unit root test on F_t $\left(ADF_{\hat{F}}\right)$ is simply the standard augmented Dickey Fuller test of non-stationarity in single time series. Critical values at 5% level are-2.86 with constant, -3.41 with constant and trend.

The p-values of individual-specific ADF tests on the idiosyncratic terms e_{it} are pooled ($P_{\hat{e}}$) in the Maddala and Wu test (1999) and this test is standard normally distributed. $H_0 : \rho_i = 1 \; \forall i$ against $H_1 : \rho_i < 1$ for some i.

Table 4. Cointegration test: Bai and Ng (2008).

Cointegrating relationship accounts for correlation between factor and explanatory variable. MSB test applied to residuals.

POOLED TEST	
$\sqrt{3}N^{-1/2}\sum_{i=1}^{N}\left(MSB_i - 1/2\right)$	2.15

Note : Cointegrating relationship estimated using CupBC. Code supplied by Serena Ng. Test statistic is standard normally distributed and test is two-tailed.[11]

[11] Private correspondence with Kaddour Hadri, Joakim Westerlund and Serena Ng.

Table 5. Testing causation between income and health

	Y life expectancy X GDP per capita		Y GDP per capita X life expectancy	
	One lag	Two lags	One lag	Two lags
$\hat{\alpha}_1$	0.094656 ** (0.040971)	0.325696 ** (0.037007)	0.628016** (0.032737)	0.129506** (0.038793)
$\hat{\alpha}_2$		0.087399 ** (0.037938)		0.480391 ** (0.039073)
$\hat{\beta}_1$	0.037951** (0.004826)	0.014552 ** (0.005578)	0.770575** (0.273715)	0.534788 ** (0.264127)
$\hat{\beta}_2$		0.020411** (0.005462)		1.670905** (0.260320)
$\hat{\gamma}$	-0.176967** (0.033132)	-0.187034** (0.031222)	-0.1209949** (0.020282)	-0.126321 ** (0.019802)
$\hat{b}_{CupBC}$	0.017561** (0.007893)	0.017561** (0.007893)	5.192215** (0.426865)	5.192215** (0.426865)
$\hat{b}_{CupFM}$	0.018797** (0.004595)	0.018797** (0.004595)	5.270640** (0.279457)	5.270640** (0.279457)

Note : Model $\Delta Y_{it} = \sum_p \alpha_p \Delta Y_{it-p} + \sum_p \beta_p \Delta X_{it-p} + \gamma\left(Y_{it-1} - a_i - bX_{it-1} - \lambda_i F_{t-1}\right) + u_{it}$. [12] Estimation carried out using OLS. Standard errors given in parentheses. Statistical significance at the 1% and 5% levels are indicated by '**' and '*' respectively.

[12] The argument for not introducing a common factor term outside of the cointegrating relationship is analogous to the treatment of deterministic terms in an ECM. Here, it would induce a type of common stochastic trend in the data. Such a trend is already allowed for in the specification of the long-run relationship. The addition of a common factor term outside of the cointegrating relationship is therefore considered superfluous.

Table 6. Non-stationarity, cointegration and causation for other health measures

		Life expectancy at birth, Total	Life expectancy at birth, male	Life expectancy at birth, female	Life expectancy at age 60, male	Life expectancy at age 60, female	Infant mortality
	N	13	13	13	13	13	24
	T	48	48	48	48	48	48
With constant	$ADF_{\hat{F}}$	-1.468	-0.524	-2.108	1.860	-0.200	0.078
	$P_{\hat{\varepsilon}}$	1.216	1.361	1.493	-1.400	-1.719	-4.349
With constant and trend	$ADF_{\hat{F}}$	-1.495	-1.808	-1.330	-2.375	-1.471	-3.286
	$P_{\hat{\varepsilon}}$	0.252	0.025	0.803	0.048	0.584	0.624
Cointegration test		2.78**	1.79	1.80	3.93**	4.71**	-1.28
Causation	$\hat{\alpha}_1$	0.140 **	0.147 **	0.135 **	0.188 **	0.157 **	-
	$\hat{\alpha}_2$	0.499 **	0.510 **	0.496 **	0.538**	0.515 **	-
	$\hat{\beta}_1$	0.562**	0.379	0.584**	0.041	0.221 *	-
Y GDP per capita X life expectancy	$\hat{\beta}_2$	0.764**	0.684**	0.858**	0.210**	0.301**	-
	$\hat{\gamma}$	-0.132**	-0.133**	-0.131**	-0.221**	-0.150**	-
	$\hat{b}_{CupBC}$	3.729**	3.194**	4.133**	1.437**	1.326**	-
	$\hat{b}_{CupFM}$	3.742**	3.218**	4.133**	1.420**	1.356**	-
	$\hat{\alpha}_1$	0.400**	0.396 **	0.388 **	0.218 **	0.182 **	-
	$\hat{\alpha}_2$	0.200**	0.183 **	0.206 **	-0.070	-0.077	-
	$\hat{\beta}_1$	0.017**	0.022**	0.019**	0.071**	0.062**	-
Y life expectancy X GDP per capita	$\hat{\beta}_2$	0.015*	0.015*	0.011	0.046**	0.054**	-
	$\hat{\gamma}$	-0.192**	-0.161**	-0.192**	-0.226**	-0.216**	-
	$\hat{b}_{CupBC}$	0.015	0.014	0.009	0.012	0.013	-
	$\hat{b}_{CupFM}$	0.015*	0.014	0.010	0.014	0.013	-

Note : Model $\Delta Y_{it} = \sum_p \alpha_p \Delta Y_{it-p} + \sum_p \beta_p \Delta X_{it-p} + \gamma\left(Y_{it-1} - a_i - bX_{it-1} - \lambda_i F_{t-1}\right) + u_{it}$. Estimation carried out using OLS. Two lags were used in all regressions. Statistical significance at the 1% and 5% levels are indicated by '**' and '*' respectively.

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