Is there an Association between Medical Research and Development and Health?

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Abstract

This paper establishes the claim that there is a relationship between medical R&D and improved health using data from the UK. There is a growing literature where simulation exercises are undertaken to express the potential health benefits of medical R&D. These are purely simulation exercises and much is assumed in these relationships. This study is the first to establish some direct statistical association at the aggregate level between medical R&D and aggregate health indicators. Using UK time series data and changes life expectancy to quantify health this study establishes a statistical relationship at the aggregate level between health and medical R&D. Results are based on an aggregate production function approach, and are qualified by the fact that the precise mechanisms through which such a relationship is established is not defined. The results are empirical and show a positive gain to UK medical R&D with a percentage change on the rate of growth of cumulative R&D over the period 1961-2010 of 0.3 with respect to changes in life expectancy gains at birth.

1. Introduction

This paper establishes the claim that there is a relationship between medical R&D and improved health using data from the UK. The measurement of the return to medical R&D is moving up the policy agenda as both public and private expenditure on this component of R&D grows. While it is difficult to measure comparatively medical R&D has been growing in a number of countries. Although the absolute base of health related R&D expressed as a percentage of GDP for example is small, with the USA spending the largest amount (approximately 0.25% of GDP in 2005), within the OECD the average annual growth rate of health related R&D has increased rapidly and over the period 2000-2006 is estimated to have been approximately 7.5% (OECD, 2008). The UK spends a little under 0.2% of its GDP on health related R&D. Currently such expenditure amounts to approximately £7 billion per annum and is split roughly 50:50 across public and private sector contributions. In the former case the funds are largely financed by government bodies, although with significant contribution from various medical charities, while the vast majority of the private sector funds are derived from the pharmaceutical industry.

Remarkably little is known about the derived benefits from these investments. Intuitively these gains may be assumed to be relatively high given the increase in average life expectancy and, arguably, quality of life over the recent past. In the UK the increase in life expectancy among older adults, the population with most to gain from improved health care interventions, has been particularly dramatic in recent years. Between 1980-82 and 2004-06 life expectancy at age 65 increased by 4.0 years for men and 2.8 years for females. At the other end of the age spectrum improving mortality rates mean that the chance of a new born boy reaching age 65 has increased from 74 per cent to 84 per cent over the same period. While for females the chance has increased from 84 per cent to 90 per cent. Such gains of course are partly attributable to improvements in general living standards, but undoubtedly also reflect to some extent the use of health care improvements, which in turn may be attributed to medical R&D expenditures. Moreover these indications of return take no account of improvements in quality of life gained through morbidity improvements.

Recently there have been various attempts to calculate the social returns to health R&D expenditure, however most have relied on simulation models to estimate these gains. In particular value of life estimates and rate of return methodologies have been used in such simulations.[1]

Perhaps the most comprehensive approach relates to a number of recent papers by Murphy and Topel [e.g. 2001; 2006] who have attached a monetary value to the gain in life expectancy as a means of quantifying the return to medical R&D. The basic approach adopted by Murphy and Topel draws on an established literature suggesting that individuals would be willing to pay a monetary sum to reduce the risk of mortality. Estimates of the values attached to reductions in these risk levels extrapolate to an estimate of the value of a (statistical) life. The formulation of the WTP for changes in the risk of dying is then related to the utility (welfare) gained from wealth under different mortality risks. The basic equation which drives empirical estimation is thus based on an individual's willingness to pay for avoidance of death set equal to the monetarised value of the welfare gained through living, with this second term essentially equal to discounted lifetime wealth, leisure and consumption activities. On this basis, using $5 million as the value of a statistical life, they estimate that post-1970 gains in welfare are a substantial $3.2 trillion per year (approximately 50% of US GDP per annum). While not all of this reduction can be attributed to R&D into health care they do further estimate that a 1% reduction in mortality from cancer would be worth $500 billion. McGuire and Raikou (2007) replicating their approach for the UK, estimate that the value of improved longevity in the UK is £2.6 trillion as a total for the period 1970-2000. Scaling up the population size and using a value of life estimate closer to the American figure the two studies' estimates are roughly comparable, indicating the impact that the estimates used in such simulations have on the resulting conclusions.

In a related study Luce, Mauskopf, Sloan et al (2006) estimate the return on investment in health from 1980 to 2000 for the USA. The authors use a value of $4 million for a statistical life as the basis of converting improved US mortality rates over the period 1980-2000 to

[1] Other approaches have been extensively reviewed, (cf UK Evaluation Forum, 2006). The pay-back approach is essentially a rate of return methodology applied to specific research interventions (Townsend et al 2003). The health outcome achieved can be measured in a number of ways. One measure relates the research implementation costs to returns in terms of QALYs which can be monetarised through the threshold level adopted or implied by health care regulators. Recently this pay-back approach has also been contrasted with, and to a degree validated by the Expected Value of Information method as applied to single trial interventions (Fleurence, 2007).

estimate the monetarised return from health care expenditures over a similar period. They calculate three different returns based on the ratio of annual increased expenditures on total health care services in the USA over the period relative to the monetarised value of mortality reductions, the ratio of annual increased expenditures on total health care services in the USA over the period relative to the monetarised gains attributable to mortality reductions in four specific disease areas (heart attack, stroke, Type 2 diabetes and breast cancer), and a ratio based on expenditure on selected major treatment improvements relative to the monetarised gains attributable to mortality reductions in the same specific disease areas. On this basis they calculated that for each dollar ($1) spend on health care the returns were in general $1.55 to $1.95 under a range of assumptions; and $1.10, $1.45; $1.55 and $4.80 for a dollar spend on heart attack, stroke, Type 2 diabetes and breast cancer respectively. While for specific treatment innovations the rate of return on a health care dollar spent ranged between $1.12 and $38.00. Using a similar approach but a different measure (QALYs) Cutler and McClellan (2001) have estimated an overall rate of return on a dollar spent on US health care over the period 1950 to 1990 to be $3.71 which, given that their calculated return includes quality as well as length of life, is consistent with the Luce et al findings. Their figure increased greatly when applied to specific diseases. A recent UK study estimates, in a similar fashion, the return to CVD research in the UK to be 9% over the period 1989-2005 in terms of QALYs, with the public sector and charitable R&D earning an internal return of 0.39% (39p) per year on each £1 invested (HERG et al, 2008).

There has of course been criticism of such “value of life” based rate-of-return studies relating to the underlying general assumptions used to retrieve empirical estimates. Not only are such simulations assumption led, but criticism has also been leveled at the estmates used. Some have highlighted the ability of individuals’ to understand the use of risk premia in this context, the framing of questionnaires and the widespread use of WTP measures estimated for specific changes in mortality that are then extrapolated to different forms of mortality risk reduction (see Viscusi and Addy, 2003). Indeed some argue that general value of life estimates, drawn mainly from labour market studies in the USA, should not apply to the health care sector where the methodology based on human capital is inappropriate and where considerable externalities, exhibited by family and friends, may exist (Becker, Murphy and Philipson, 2007). All such studies simulate such results based on numerous modelling assumptions that are required to generate rates-of-return in a meaningful base to compare to the monetary amounts invested in R&D.

Importantly then such simulations assume rather than determine the relationship between medical R&D expenditures and health outcomes. The present study represents an attempt to examine whether a statistical relationship between medical R&D expenditures and health outcomes actually exists, which would at the very least lend some empirical support to the assumptions used in the existing calculations on the return to medical R&D. To establish this long-run relationship the stationarity properties of the relationship between the variables medical R&D expenditure and a particular measure of health outcome, changes in life expectancy are investigated. Necessarily the relationships are investigated at an aggregate level, through the use of an aggregate production function.

2. Data, methodology and model

The approach adopted is to specify a data generating process between UK medical R&D, GDP per capita, health expenditure per capita and various measures of health outcome over time. The aim is to determine whether a long-run relationship between medical R&D and health outcome can be established statistically. Accordingly data, as described below, were gathered for the period 1961-2010 and modelled based on an aggregate production function. We assume a basic Cobb-Douglas function and model production of health as:

$$H = Af(K, L)$$

Such that:

$$H_t = AK^{\alpha}L^{\beta}$$

The level of technology is proxied by assuming $A = f(R \,\&\, D^{stock})$. Thus R&D stock defines technical change and is considered Hicks neutral; such that shifts in the production function are scale changes and, for given relative factor prices, R&D will leave the K/L ratio unchanged. R&D acts as a shift parameter. This may be considered a strong assumption but given the relatively fixed factor component of much of health care it may not be as strong as first consideration would suggest. We can further add a time trend to capture all other effects that surely have affected life expectancy other than health care, t, and a constant ϕ, to capture residual production effects. Applying logarithims to the variables of interest we can estimate the production function:

$$\ln H_t = \phi + \lambda t + \alpha \ln K_t + \beta \ln L_t + \varphi \ln(R\&D_t^{stock}) + \varepsilon_t$$

We are interested in the returns to R&D. We can return these by focussing on first differences, which as we will see is statistically convenient in any case, such that we have:

$$\ln \Delta H_t = \lambda + \beta \Delta \ln L_t + \beta \Delta \ln K + \varphi \Delta \ln(R\&D_t^{stock}) + \Delta \varepsilon_t$$

This essentially returns the growth equation.[2]

Analysis of times series data is complicated, not least as past values and common trends may affect the underlying time-path of the variables under study. If not accounted for correctly associated problems of autocorrelation and de-trending of series will result in biased, possibly spurious estimates of association. Standard regression techniques require that the variables be covariance stationary; which implies that their mean and all autocovariances are finite and constant over time. Covariance-stationary processes are defined to be an integrated process of order 0, or I(0) (Enders, 2004). If the variables in levels are not covariance-stationary but their first differences are, the series is deemed to be an integrated process of order 1, I(1). Note however that multivariate regression based merely on first differencing of the variables under such circumstances will result in misspecification error as it excludes the long-run equilibrium relationships which hold among the variables. With misspecification error the regression estimates and all statistical

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[2] Further simplification is allowed by noting, as Kafouros (2004) does, that the parameter φ is the elasticity of R&D, $[\frac{\delta H}{\delta(R\&D_t^{stock})}.\frac{R\&D_t^{stock}}{H}]$, while $\Delta(R\&D^{stock})$ may be defined as $\frac{R\&D_t^{flow}}{R\&D_t^{stock}} = \frac{\delta(R\&D_t^{stock})}{R\&D_t^{stock}}$, so $\varphi \ln(R\&D_t^{stock})$ can be re-written as $\frac{\delta H}{\delta(R\&D_t^{stock})}.\frac{R\&D_t^{stock}}{H}\frac{\delta(R\&D_t^{stock})}{R\&D_t^{stock}}$ or with simplification as $\frac{\delta H}{\delta(R\&D_t^{stock})}.\frac{\delta(R\&D_t^{stock})}{H}$. Assuming we may treat $R\&D_t^{flow} \approx \delta(R\&D_t^{stock})$, and that investments in R&D do not depreciate, as is arguably true with health investments, our estimation equation can be re-written as

$$\ln H_t = \lambda + \beta \Delta \ln L_t + \beta \Delta \ln K + \gamma \Delta \frac{R\&D_t^{flow}}{H_t} + \Delta \varepsilon_t$$

where the marginal rate of return to R&D, γ, may be estimated. This is not pursued here.

tests will not be representative of the true underlying statistical process that holds across the variables. The appropriate manner to establish a statistical relationship is to test for linear combinations of integrated variables that are stationary. If found such variables are said to be cointegrated and this then allows for the implementation of statistical procedures that can identify, under certain assumptions, consistent estimates of the long-run statistical association between stochastic variables. Integrated processes of higher order than I(1) can be examined in this manner through further differentiation but inference and interpretation becomes increasing difficult. If on the other hand the variables are not cointegrated with rank I(0) then OLS suffices. As the results will show we have data which confirms to rank I(0).

There are a number of cointegration approaches. The earliest approaches are associated with Engle and Granger (1987) and based on single equation estimation. It transpires that the specification of the single equation, essentially whether Y=f(X) or X=f(Y) matters in the determination of cointegration.[3] Moreover when there are more than two variables there may be more than one cointegrating relationship, and the Engle-Granger approach, which uses residuals from a single relationship is unable to identify more than one cointegrating relationship. This obviously constrains the number of cointegrating vectors. This led to the introduction of the Vector Autoregressive based cointegrating models by Johansen (1991). The Johansen procedure allows higher levels of cointegration, but proceeds through various complex steps which may or may not be able to identify the structural cointegrating relationships in the specified system of equations. If they are to be identified it requires that all cointegrating relations have the same rank. This is a binding constraint and recent work by Pesaran and Shin (1999) and Pesaran et al (2001) has developed the Autoregressive Distributed Lag (ARDL) model to estimate cointegrated structures where the rank may differ across the variables. This bounds testing approach also assumes that all variables are endogenous. We adopted this more general approach to examine the health care production relationship.

There is no widely agreed aggregate measure of health outcome with a long-time series. Life expectancy is the most obvious candidate but this ignores improvements in morbidity. Life expectancy can be calibrated against different ages, sexes and diseases. In this exploratory paper we use life expectancy at birth as the preferred measure of health

[3] At the asymptote this is not the case, but for small samples (as is the norm in time series) the test for cointegration, which rests on examination of the residuals, will be affected by the specification.

outcome, noting that this will underestimate health gains as it is a mortality based measure.

To trace labour and capital over time we use the numbers employed in the UK NHS and the levels of capital expenditure as taken from UK National Accounts. There are many, obvious drawbacks in their use. For labour the total numbers are a proxy for the level of service provided and do not discriminate, for example, between different skill mixes, part-time and full-time work and differences in working hours over time. For capital the use of expenditure levels does not take account of service flow per period of time or depreciation. They both serve as readily available proxies.

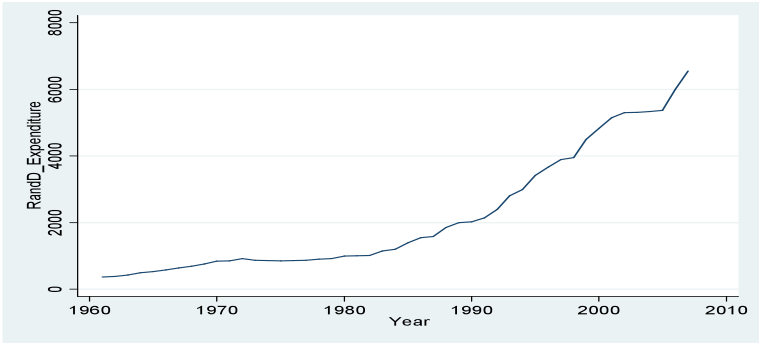
A consistent data series on medical R&D expenditure is even more difficult to collate. First medical R&D expenditure in the UK comes from three primary sources: the government, charitable institutions and the private sector. Even the government based R&D is associated with a number of public sector bodies including governmental departments, research councils and, for some time periods individual National Health Service (NHS) bodies. Second, there has been no previous attempt to consistently match such series across these sectors over time, particularly for the pharmaceutical industry. Third while consistent it is clear that the series is not complete. That said, the overall trend appears to match a priori expectations and, for relevant periods, fits with the data collected by other sources for a sub-sample of years (HERG et al, 2008). Moreover it is, if anything an under-estimate as it has proven impossible to collect all R&D expenditure from either government or small charitable organisations over time. Data on R&D were collected for the three primary sources first and then collated. Governmental R&D expenditures where collected from 1960-1972 from the UK Central Statistical Office and exclude social science and central government contributions to medical R&D (CSO, various years). From 1972-1980 governmental R&D expenditures come from the annual Department of Health and Social Security R&D reports, which represents the majority of medical R&D but is non-inclusive of NHS funded research or educational payments to fund medical R&D[4]. From 1980 onwards data were taken from various OECD reports on R&D expenditure levels, which in turn were based on UK governmental returns. R&D expenditure by charitable organisations

[4] Data were collected on NHS expenditure but this was possible only for the years 1975 onwards from various sources. Similarly it was not feasible to track university expenditure devoted to medical R&D. This probably means that government R&D expenditure is underestimated by approximately 50%. To the extent that the proportionate relationship between the rest of government R&D expenditure and NHS and university medical R&D expenditure is roughly constant over time, as it is for the period 1982-1992 where we have the most consistent series (proportion of used governmental R&D to NHS plus university estimates of medical R&D lie between 0.47 and 0.58 here) this should not affect our results. The increase in the degrees of freedom back to 1961 for the majority of data dictated NHS and medical R&D was not recorded separately in the data set.

were based on Reekie (1975) for the years 1961-1963. From 1963 until 1988 expenditure levels were based on Wellcome Trust annual reports supplemented by Thompson (1973), who has undertaken a substantial history of the UK Medical Research Council, and therefore confined largely to this charity (which remains the dominant medical charity within the UK). Expenditure figures were reported in two-year bands by the Wellcome Trust over this period and an average was calculated to produce annual expenditures. From 1988 until 1995 the Association of Medical Charities annual reports were used as the basis of charitable medical R&D expenditure. From 1995 onwards various Parliamentary reports, Association of Medical Research Charities reports and individual charity reports were used to produce expenditure levels for individual years. For the private sector, where medical R&D is dominated by the pharmaceutical industry, earlier studies by Reekie (1975) and Prentis and Walker (1988) were used for the expenditure levels between 1961 and 1983. From 1984 onwards various reports of the Association of the British Pharmaceutical Industry were used as sources for annual expenditure on R&D.[5] All expenditure data are deflated by the GDP deflator.

Figure 1 shows total medical R&D expenditure per annum over the period 1961-2006 for the UK. As can be seen the general trend gained from collation of data from these sources is relatively stable and consistent over time. An exponential growth in R&D expenditure is seen to have taken place over this period with slight levelling off in the early part of this century, followed most recently by a re-galvanisation consistent with the current plans to increase total governmental R&D, including medical R&D, to 2.5% of GDP by 2014, as well as a matching of public sector expenditure by pharmaceutical expenditure. Of course the general smoothness of trend and exponential trend do not confirm that the data have been correctly specified, but the fit with *prior* expectation is at least of some comfort.

Figure 1 UK Medical R&D expenditure since 1961



[5] Full documentation of all sources and full data are available from the authors.

Table 1 presents the average values of the main variables in our sample which runs from 1961 through 2010.

Table 1 Summary Statistics

	Mean	Minimum	Maximum
Life expectancy	74.8	70.6	80.4
Cumulative medical R&D	£35billion	£0.4billion	£123billion
NHS workforce (fte)	914,723	528,234	1,313,230
Capital	£2,353million	£0.7million	£6,055million

3. Empirical findings

As noted above cointegration reflects the existence of a stationary linear combination of non-stationary variables in the statistical model. A prior requirement to estimation through cointegration therefore is that data be tested for stationarity in levels and first differences. A number of tests for stationarity, based on the presence of unit roots over time in the data, were conducted including the Dickey-Fuller test (Dickey-Fuller, 1981), the augmented Dickey-Fuller test and the Phillips-Perron test (Phillips, 1986; Perron, 1990).[6] While 1961 to 2010 gives a total of 49 years, once long lag times are included degrees of freedom are quickly diminished. The first stage in estimation was therefore to define the preferred lag structure to impose on the variables both to implement the tests for stationarity, but also as the specification of the lag structure is in any case required for the cointegration procedure itself.

It is assumed that the lag structure associated with R&D effects on health will vary from those of labour and capital. The adopted cointegration procedure, based on ADRL models allows for varying lag lengths. A long lag length was assumed for R&D and this was adopted for the tests undertaken as a means of determining optimal lag length. A variety of tests were used to determine lag length including a final prediction error test, Schwarz's Bayesian information criteria, the Hanna-Quinn information criteria and the Akaike information criteria (Akaike, 1973; Lutkepohl, 2005). Selection of too few lags can result in the regression residuals not behaving like white-noise processes, while too many lags results in over-parameterization and a further loss of degrees of freedom. The final

[6] A stationary series tends to return to its mean value and has finite variance. If the unit roots of any equation are greater than unity in absolute value, the (time) series arising from this equation will be stationary. But note these tests are based on stochastic processes and testing for unit root, not stationarity itself; that is they encompass error.

prediction error criteria uniformly selected lag lengths that were slightly shorter than the other criteria and with the lack of any other form of empirical data to inform choice, and noting that the presence of unnecessary lags influences the power of the Dickey-Fuller test to detect a unit root, that the prediction error criteria have a tendency to overestimate the lag structure and that the white-noise status of the errors will be reviewed in later tests, the lag structure was based on this test (Lutkepohl, 2005). Lag length of 17 years was routinely indicated by these tests of R&D as it impacts on life expectancy. Selection of too few lags results in the errors not being white noise, while too many lags over-parameterise and leads to a loss of degrees of freedom.

The Dickey-Fuller and the Phillips-Perron tests were then all conducted on the variables specified in logarithms and each test assessed stationarity in levels and differences. The tests indicated stationarity in first differences for all the variables, but that the cumulative R&D series is also stationary in (log) levels. This is not an uncommon inconsistency. The Dickey-Fuller tests are known to have very limited small sample properties with a tendency to reject stationarity. In general unit root tests suffer from poor size and power properties. It is therefore reasonable to be cautionary and accept that the series are non-stationary in levels but stationary in first differences. Overall the Phillips-Perron tests suggest that the series are therefore non-stationary in levels, I(1), and stationary in first differences, I(0). We proceed on this basis.[7]

Table 1 Unit root tests on Life Expectancy (LE), Labour, Capital and Cumulative Medical R&D (CumRD) expenditure in (log) levels and first differences

	Dfuller	Perron		
lnLE	1.063	2.265		
LnLabour	-2.227	-1.725		
LnCapital	-1.513	-1.567		
LnCumRD	-9.029	-5.731		
LnD.LE	-10.725	-11.622		
LnD.Labour	-2.953	-2.896		
LnD.Capital	-7.788	-7.737		
LnD.CumRD	-22.657	-16.336		
		1%	5%	10%
DF-critical value		-3.58	-2.93	-2.6
P-critical value		-3.594	-2.936	-2.602

[7] Although as noted above the ARDL approach does allow for different degrees of integration.

Having tested for unit roots and accepted that the series are I(0) and stationary in first differences we return to our estimated equation where *H*, health status is represented by life expectancy at birth, labour input (L) is full-time equivalents, capital (K) is real annual expenditure and *R&D* is accumulated real expenditure on research and development within the medical sector and includes public sector, charitable and private (essentially pharmaceutical) expenditure. We impose 17 and 18 years of lag on the R&D variable.[8]

$$\Delta \ln LE_t = \lambda + \beta_1 \Delta \ln L_t + \beta_2 \Delta \ln K + \varphi \Delta \ln(R \,\&\, D_t^{stock}) + \sum_{t-1} \gamma \Delta \ln LE + \sum_{t-1} \gamma \Delta \ln L + \sum_{t-1} \gamma \Delta \ln K + \sum_{t-1}^{t-18} \gamma \Delta \ln(R \,\&\, D^{stock}) + \Delta \varepsilon_t$$

Table 2 reports the results of the cointegrating parameters for assumed lag lengths of 17 and 18 years on R&D expenditure, with our preferred structure being 17 years lag as indicated by the various tests. The results suggest a 1% rise in the growth rate of R&D would increase the gain in average life expectancy at birth by 0.3 years.

Table 2 Estimates of the Long-Run Cointegration Relationship

Constant	0.001	-0.314	-0.008	0.028
d.LE	-0.005	-0.005	-0.007**	-0.007**
	(-0.003)	(-0.003)	(-0.002)	(-0.002)
d.Labour	0.028	0.121	0.012	0.029
	(0.043)	(0.24)	(0.38)	(0.039)
d.Capital	0.004	0.006	0.012**	0.011
	(0.006)	(0.007)	(0.005)	(0.005)
d.R&D	0.336**	0.356**	0.306	0.292
	(0.165)	(0.201)	(0.222)	(0.228)
Year fixed effects	No	Yes	No	Yes
Lag R&D	18	18	17	17
N	31	31	32	32
adj. R-sq	0.41	0.39	0.32	0.3
F	36.15	14.2	8.92	7.41

To investigate whether the long-run relationship holds Pesaran et al (2001) suggest a bounds test based on a Wald test (F-test) on the following hypothesis: that the coefficients on the non-lagged variables, i.e. the coefficients $\beta_1, \beta_2, \varphi$ are all equal to zero, indicating no

[8] Longer lag lengths resulted in over-parameterisation; shorter lags did not much alter the results

cointegration versus the alternative that they are jointly not equal to zero, indicating cointegration. An upper limit, reflecting a value indicating cointegration, and a lower limit, indicating no cointegration are given by Pesaran et al (2001). If the value is greater than the upper value there is cointegration, if below there is no cointegration and in the mid-range it is indeterminant. The relevant critical values are 2.79 for the lower limit and 4.10 for the upper limit (Table C(iii) Pesaran et al (2001)). The returned F-value of 4.73 indicates an cointegrating relationship between the variables life expectancy at birth, labour, capital and R&D in first differences.

While the cointegration relationship must hold in the long-run, there may be short term deviations from the long-run equilibrium. These may be modelled through an error correction process. The short run error correction model, representing the shocks to the long-run equilibrium is presented in Table 4. The error correction model is given as:

$$\Delta \ln LE_t = \lambda + \beta \Delta \ln L_t + \beta \Delta \ln K + \varphi \Delta \ln(R \& D_t^{stock}) + \Delta \varepsilon_{t-1} + \nu$$

With all variables defined as above except for the $\Delta \varepsilon_{t-1}$ which is the error correction component estimated from the cointegrating relation. The error term is negatively signed which guarantees return to the long-run relationship, but does not attain statistical significance.

Table 4 Error Correction estimates

d.lnLabour	0.0182
d.lnCapital	0.007**
d.lnCumR&D	0.002
e(t-1)	-0.497
constant	0.001
n	30
Adj R-2	0.086

4. Conclusions

As noted in the introduction there is a growing literature where simulation exercises are undertaken to express the potential, assumed health benefits of medical R&D. Many are purely deterministic in nature and much is assumed in these relationships. Obviously while there are a multitude of individual clinical trials or other forms of medical research in which health benefits are directly achieved, the aggregate productivity of medical R&D on health outcomes has never been established. Indeed there is some evidence to support the view that beneficial medical R&D may not be fully translated into the more heterogeneous populations serviced by health care generally or that it may take some years before such benefits are realised (cf. Haines and Donald, 1998 for a detailed discussion). Thus it is perhaps not surprising; especially as R&D expenditure inevitably encompasses elements of failure as well as success, that establishing such an aggregate relationship is complex. This study is the first to establish some direct statistical association at the aggregate population level between UK medical R&D and an aggregate health indicator.

Establishing these aggregate relationships is, as just noted complex and they have proven difficult to establish. This particular study was limited by small sample sizes, the definitions of the aggregate health indicators and the level of aggregation at which the analysis was conducted. The indicator used is life expectancy, which has obvious shortcomings. It is undoubtedly the case that medical R&D also impacts upon morbidity, probably to a greater degree than mortality, but it has proven unsuccessful to quantify this benefit. The necessary empirical data on morbidity do not exist. The possibility of using recorded days of sickness from work was explored but the data series did not reach far enough back in time to allow estimation of a suitable form, as undertaken above, to be pursued. As such the aggregate effect of medical R&D on the population is both confounded and dissipated by many factors.

Moreover, it is likely that the true relationship between life expectancy and R&D is non-linear in nature and that full specification of the production process of which it forms part would include other, omitted variables. Recent work by Hall, Swamy and Tavlas (2012) outline a cointegrating strategy which handles non-linearities, allowing a maximum benefit to life expectancy, and omitted variables that is clearly applicable to the issues at hand here. Thus our results should be considered a first approximation. The more general approach is clearly of interest given the various biases that may occur in estimating returns to R&D including the influence of spillover effects, depreciation on R&D itself, and various

measurement and statistical issues (see Hall, Mairesse and Mohnen, 2009). Although given that life expectancy at birth increased on average by 1.1 years over the period 2004-2006 to 2008-2010 (ONS, 2011) and that there the geographical difference in life expectancy across the UK grew from 12.5 to 13.5 for males and 10.1 and 11.8 for females over this period even the extrapolation of our results appear feasible. Clearly caution must be exercised here; the mechanism at work across inequality and R&D productivity obviously differ.

A clear conclusion to evolve is that if interest continues in these aggregate relationships, effort should be made to continue to collect and collate consistent time series data on medical R&D and on a series which would reflect morbidity impact. Clearly further research is required to validate the productivity of medical R&D expenditure. A major positive advance made here is that for the first time a statistical association links UK medical R&D expenditure to a positive health outcome at an aggregate level.

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