Postwar Mortality Decline and Economic Growth in Industrialized Countries: A Puzzle

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Abstract

Both life span and income are key dimensions of well-being, and they are also essential products of economic growth and development. Other things equal, theory suggests that similar economies should accumulate life span and income in similar proportions. But the last several decades have brought uneven patterns in relative accumulations of income and life expectancy among industrialized nations. This paper documents heterogeneous combinations of economic growth and mortality decline among 14 high-income countries since 1960, and it shows that they cannot be explained by any of the available time-series data: education, income inequality, health spending, smoking, or diet. Why some rich countries are becoming longer lived and presumably healthier on average than others is an unresolved puzzle that future research efforts must address.

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Introduction

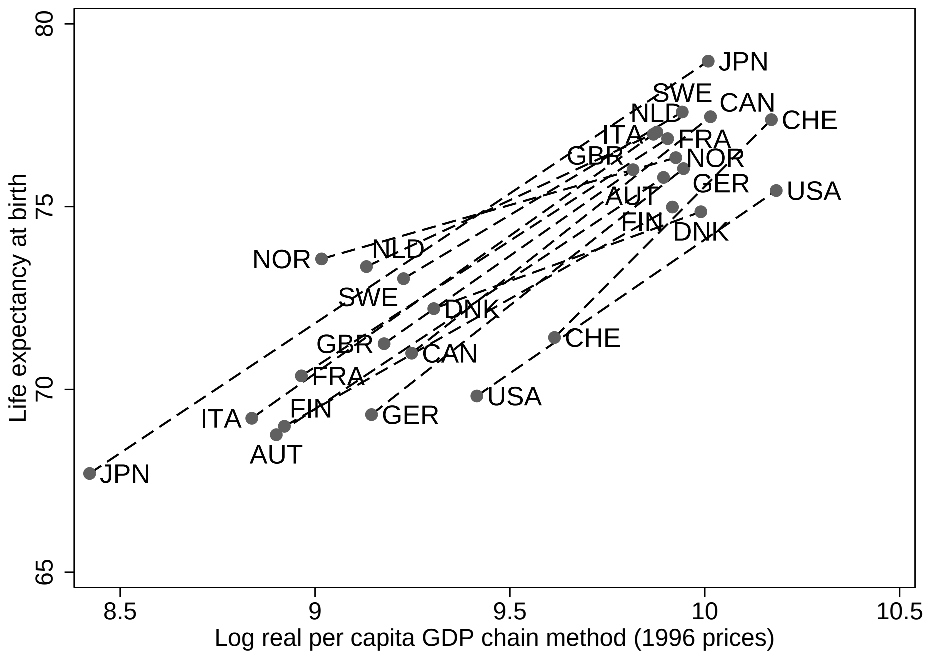
This is a paper about convergence in well-being among similar countries, about a discrepancy in the relative accumulations of two key aspects of well-being, and about the limits to our knowledge regarding how life span is produced. While theory suggests that income and health should be interrelated, I demonstrate how growth in per capita income has not synchronized with increases in life expectancy among industrialized nations since 1960, even though there is evidence of convergence among rich countries in each variable separately. Individuals in some advanced nations are increasingly living longer than those in others, even though their incomes are growing similarly. Put another way, the joint distributions of income and life expectancy are not converging, although the marginal distributions are.

I depict these dynamics in Figure 1, which plots combinations of log per capita income, y, and life expectancy at birth, e_0, among 14 high-income countries in 1960 and 1990, with dashed lines connecting the average trajectories of countries across time. If income and life expectancy were jointly converging in levels, which is typically called absolute convergence, we would expect all the dashed lines to meet in a single point in the northeast corner of the figure, with different slopes and lengths depending on the relative levels of y and e_0 in 1960. If instead there were joint convergence in growth rates and not in levels, a condition known as conditional convergence, we would expect to find a fixed arrangement of countries in (y, e_0) space over time, and thus identical slopes and lengths of the lines. Neither type of convergence is evident in Figure 1, which shows markedly different slopes, much persistent dispersion, and changes in the relative positions of countries within the cloud.[1]

Taken individually, the spreads in income or life expectancy in Figure 1 do appear to have narrowed. Such patterns support convergence, but only in the marginal distributions of y and e_0 separately. That type of convergence has been extensively studied and documented. Dowrick and Nguyen (1989) describe strong postwar patterns of income convergence among OECD countries, for example, while White (2002) has shown similar evidence for life expectancy. Without seeing Figure 1, in fact, one might be tempted to con-

[1]Comparing more recent years, such as 1980 and 1990, yields qualitatively identical results. The relative positions of countries in the distribution of life expectancy and in the distribution of income per capita have changed in strikingly different ways in each decade since the Second World War.

Figure 1: Trajectories of life expectancy and log per capita income, 1960 and 1990



Notes: Dashed lines connect observations across time for a particular country and do not represent data in intermediate periods. True trajectories are slightly convex in $(y, \mathbf{e}_0)$-space for most countries in the panel. Data are taken from the Human Mortality Database (HMD) and the Penn World Tables 5.6 and 6.1. Country abbreviations are as follows: Austria (AUT); Canada (CAN); Switzerland (CHE); Denmark (DNK); Finland (FIN); France (FRA); United Kingdom (GBR); Germany (GER); Italy (ITA); Japan (JPN); Netherlands (NLD); Norway (NOR); Sweden (SWE); United States (USA).

clude that convergence in y and convergence in e_0 implies convergence in the joint distribution, but we have seen that this is incorrect. Should the odd behavior of the joint distribution of income and life span among industrialized countries concern us?

In a wider cross section of countries, similar patterns of growth in life expectancy without corresponding increases in income are seen as positive developments in human well-being. Wilson (2001) and Goesling and Firebaugh (2004) describe massive demographic convergence between rich and poor nations since the Second World War, although inequalities persist in sub-Saharan Africa, hard-hit by the AIDS epidemic. Becker, Philipson and Soares (2003) find that despite huge, persistent gaps in income per capita, differentials in mortality and thus in the value of life between rich and poor nations have converged, suggesting that overall human welfare has converged much more than income alone has. The mechanism behind such advances appears to have been the diffusion of health technologies, especially those combating infectious disease, from core to periphery. This result is consistent with the classic finding of Preston (1975), that technological change rather than income is the primary motive force behind temporal growth in life spans, which is echoed in more recent work by Lichtenberg (2002, 2003).

It is easy to see why mortality decline that is unhinged from economic growth is a pattern to be celebrated when it occurs in the long-deprived periphery. Good health may in turn even produce higher incomes, as found by Bloom, Canning and Sevilla (2004) and others, perhaps contributing to eventual income convergence. But what are we to make of divergent patterns in mortality decline among high-income countries in the core? There is no convenient, intuitive explanation as with the developing world regarding technology transfer. Advanced countries themselves produce new health technologies that benefit both core and periphery, and there is scant evidence of significant barriers to health technology transfer between advanced countries themselves. Lichtenberg (2003) finds that very little of the cross-sectional variation in life spans among advanced countries can be traced to the availability of new pharmaceuticals, which represent an important part of new medical technology.

Growth in life spans that is unhinged from growth in incomes among industrialized countries is fundamentally worrisome because it speaks to underlying and persistent inequalities in health that we do not yet fully understand nor know how to combat. To an extent, it is the macroeconomic analogue of a more familiar microeconomic issue: widening socioeconomic differentials in mortality whose sources are not well understood (Preston and Elo, 1995; Schalick et al., 2000). In general, we want to understand mortality differentials between distinct groups such as African Americans and whites, between those with high school diplomas and those without, or between Canadians and Americans. If they are widening without an identifiable reason, it is a cause for concern and inquiry.

As I show in this paper, no combination of the aggregate indicators that are currently available, such as income inequality, health spending, education, smoking, and diet, can satisfactorily explain why some rich countries have experienced more rapid gains in life expectancy than others, given the growth in per capita income. Without a better understanding of the sources of differential mortality decline among similar countries, we can say very little about how to capture the benefits of mortality decline, or about the future of mortality decline and mortality convergence. To the extent there may be positive feedbacks from health back into income, this gap in our knowledge may also be important for understanding income growth as well.

In the sections that follow, I first outline the theoretical background to this problem, describe the data in greater detail, and motivate my specification of a testable empirical model. Next I present econometric results in support of the main hypothesis, namely that country-specific trends in life expectancy cannot be satisfactorily explained by the available macroeconomic covariates, and I explore the robustness of my findings. The final section suggests directions for future research efforts in this area, discussing potentially key variables that we currently neither measure nor understand.

The demand for longevity

Theoretical background

The pioneering work of Grossman (1972) provides the theoretical backbone for most modern economic research into the determinants of health at the individual level. Ehrlich and Chuma (1990) extend Grossman's basic model in order to characterize an individual's demand for longevity. In these frameworks, health or longevity, e_0, is a function of a vector of demands for health inputs, $\vec{I}$; and exogenous health endowments, μ. Health inputs are determined by income, Y; prices, p; education, E; health endowments, μ; and preferences, θ, creating a system of two equations:[2]

$$e_0 = f(\vec{I}, \mu), \tag{1}$$

$$I_i = g_i(Y, p, E, \mu; \theta). \tag{2}$$

Examples of health inputs $\vec{I}$ include purchases of health care, food, and other items that affect health. These include smoking, alcohol use, exercise, and other activities that affect health that may either be market-based or not.[3]

The relative income hypothesis of Wilkinson (1992) and others suggests that an individual's relative position in the social order or in the income distribution should also affect health.[4] Relative social position may be a control variable to some extent, but the degree of social mobility is unclear. Some component of relative position may be completely exogenous, such as association with a particular racial or ethnic group. I therefore incorporate relative socioeconomic position, σ, by recasting (1) to include it as an exogenous variable:

$$e_0 = f(\vec{I}, \mu, \sigma). \tag{3}$$

As discussed by Rosenzweig and Schultz (1983), the limited availability of data on health inputs frequently precludes direct estimation of the structural equation for the health outcome, (3). Instead, researchers typically estimate what Rosenzweig and Schultz call hybrid equations, which describe health as a function of a measurable subset of health inputs, $\vec{I_m}$, along with inequality,

[2]Although there has been much recent interest among economists regarding the response of education to mortality (Kalemli-Ozcan, Ryder and Weil, 2000), I treat education as exogenous. This choice is consistent with traditional approaches and is reasonable in the cases of modern industrialized countries who have not experienced major shifts in educational attainment for many years.

[3]The act of earning income itself may have an impact on health, with the sign depending on whether it was a healthy or stressful endeavor for the individual. Research identifying effects of business cycles on worker health (Ruhm, 2000, 2003) suggests this could be an important pathway. In this paper, I make no attempt to account explicitly for job-related stress or happiness, because no internationally comparable data currently exist. Informally speaking, it seems likely that this pathway would may be very different across countries, to the extent it affects population health at all. Work-related stress among Japanese males probably exceeded that among U.S. workers during most of the sample period, yet Japanese life expectancy soared.

[4]Deaton (2003) provides an extensive overview of the topic and discusses pathways through which it might exert such an influence, such as through psychosocial stress, unequal access to capital markets, and so on.

σ, the determinants of health inputs, Y, p, E, and if available, μ and θ:

$$e_0 = h(\vec{I}_m, \sigma, Y, p, E, \mu, \theta). \tag{4}$$

Rosenzweig and Schultz note that the coefficients on $\vec{I}_m$ recovered from estimating (4) will be biased estimates of the true structural parameters on $\vec{I}_m$ in (3). We expect the magnitude and the direction of bias to depend on the exact choice of regressors in the hybrid model and how they affect the demand for health in (2).

The data and the problem

We face several difficulties deriving from the nature of the problem and the severe data limitations. If we had individual-level data on mortality and other covariates among large numbers of people in many high-income countries over spans of several decades, our task would be much easier. But such data currently do not exist, and we are effectively left only with aggregate data to inform studies of temporal changes in mortality among a set of countries.[5]

An array of problems arise with macroeconomic data. In studying industrialized countries in isolation, which are relatively few in number, I must grapple with the problem of small sample sizes. Luckily, the Human Mortality Database (2005), or HMD, provides mortality data of exceptionally high quality at annual frequencies. I therefore use annual data and linearly interpolate when necessary in order to maintain acceptable sample sizes.

Second, it is difficult to find many good measures of health inputs at the aggregate level over long periods of time. Internationally comparable measures of quantities of health care are virtually nonexistent,[6] as are measures of technology, obesity, and exercise. We are thus forced to choose between

[5]In the U.S., the National Longitudinal Mortality Study provides some insights into individual-level mortality patterns over time. Although it measures mortality and covariates in an extremely large cross section of individuals, it only covers roughly 10 years. To date, it has been primarily used to study mortality and covariates at a point in time. It is also possible to examine mortality among birth cohorts. Deaton and Paxson (2001) compare trends in U.S. and British mortality since 1950 by linking cross-sectional data on birth cohorts over time. They too find puzzling rates of mortality decline given income growth, and they suspect an omitted variable, technology, may be key for explaining trends. This suggests that data coverage may be more important than the level of aggregation once one departs from individual-level data.

[6]Available measures of health care include total spending and quantities of production inputs like hospital beds or employment, neither of which has an unambiguous relationship

two flawed estimation strategies. We can collect all available variables in a single hybrid equation, but that produces biased estimates of the structural parameters. Or we can estimate the structural equation for health with the few available measures of health inputs, but such estimates are likely to be biased by omitted variables. The hybrid equation is not immune to omitted variable bias either, of course. Without any priors regarding which method is preferable, I choose to estimate hybrid models since they seem to be more common in other aggregate studies such as Pritchett and Summers (1996) and Dowrick, Dunlop and Quiggin (1998).

A third problem with aggregation is that while variances may be important in understanding averages, little information on variances is available. In addition to the psychosocial effect that relative socioeconomic position might exert on health, inequality in health inputs could lower average population health through a Jensen's Inequality effect if the returns to health inputs are diminishing (Gravelle, 1998). Unfortunately, we have very little information on the variance in health inputs aside from income inequality. Statistics on health insurance coverage vary surprisingly little in our sample, for example. Until better measures are collected, we are stuck with income inequality as our only measure of variance in health inputs.

With these issues in mind, I proceed to specify an aggregate regression model for the hybrid equation (4) using observations since 1960 on Austria, Canada, Switzerland, Denmark, Finland, France, the UK, Germany, Italy, Japan, the Netherlands, Norway, Sweden, and the U.S. My dataset and its sources are described in greater detail in the appendix.

A testable model for aggregate data

Several changes must be made to the hybrid model before it can be estimated with aggregate data. Preston (1975) famously showed that technological change is primarily responsible for increases in life expectancy over time.

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to real quantities of health care. It is extremely difficult to disentangle quantities and prices in the health sector for one country alone (Cutler et al., 1998), let alone for a set of countries. Inputs are inferior data because technologies may differ across countries and certainly over time, implying ambiguous relationships between any one input and total output. Lichtenberg (2003) analyzes a proprietary panel dataset of pharmaceutical launches in a set of industrialized and developing countries. Coverage stretches back only to 1982, and he finds that drug launches explain an extremely small amount of the cross-sectional variation in e_0. That finding is especially telling in light of the large differences in e_0 between developed and developing countries in the dataset.

Without any good measures of technology, we must resort to alternative means to capture its effect. White (2002) finds that temporal increases in e_0 among high-income countries have been remarkably linear since 1955. A linear time trend with an error term is therefore a reasonable, parsimonious approximation to technology.[7]

Since income per capita has grown exponentially over time among high income countries, I take logs of income and similar variables. Education, smoking, diet, and inequality variables are introduced linearly. Introducing country fixed effects is a reasonable way of dealing with unobservable heterogeneity, μ, although it is unknown whether the $\mu(i)$ are actually fixed over time. If they increase linearly with time, of course, the linear time trend will incorporate their effects. But if they follow some other path, they are omitted variables. With these changes, the hybrid regression model (4) takes the following form:

$$\begin{aligned} e_0(i,t) &= \mu(i) + \delta \cdot t + \vec{\beta}_I \cdot \vec{I}_m(i,t) + \beta_\sigma \sigma(i,t) \\ &\quad + \beta_Y \log Y(i,t) + \beta_E E(i,t) + \epsilon(i,t), \end{aligned} \tag{5}$$

where i indexes countries, t indexes years, and δ is the average annual increase in e_0 due to factors like technology that are otherwise unobserved. The vector $\vec{I}_m$ includes measurable per capita health inputs like health spending, smoking, and dietary intake; σ is income inequality as measured by the Gini coefficient; Y is real per capita income; and E represents average years of education. The error, ϵ, measures shocks to technology, captures any measurement error in e_0 and the effects of all omitted variables, and it is modeled as a normally distributed IID random variable with zero mean.

Even with a time trend, estimation of (5) is plagued by extremely long-lived errors, with first-order autocorrelation coefficients close to unity. This is not surprising; we are deeply concerned about omitted variables, and that is one interpretation of serially correlated errors. In order to address autocorrelation, I examine first differences,[8] which also provides a convenient method of testing whether the model can explain divergent rates of increase in life

[7] I have also experimented with time dummy variables instead of a constant linear time trend. Results are not particularly sensitive to this choice, but the use of time dummies significantly reduces the degrees of freedom and weakens inference overall.

[8] I have also extensively tested the model using levels regressions, which were the subject of an earlier version of this paper. Although specific results may differ depending on the choice of levels versus first differences, the overall results do not change qualitatively. Country-specific time trends in levels regressions, which are analogous to country dummies

span. Taking first differences and introducing country dummy variables, $d(i)$ for country i, produces

$$\begin{aligned}\Delta e_0(i,t) &= \delta + \sum_{i\neq 1} d(i) + \vec{\beta}_I \cdot \Delta \vec{I}_m(i,t) + \beta_\sigma \Delta\sigma(i,t) \\ &\quad + \beta_Y \Delta \log Y(i,t) + \beta_E \Delta E(i,t) + \nu(i,t), \end{aligned} \tag{6}$$

where Δ denotes the change in a variable from one year to the next, and $\nu(i,t) = \Delta\epsilon(i,t)$ is assumed to be white noise. The model explains the puzzle if none of the $d(i)$ is significantly different from zero.

Estimates of (6) using ordinary least squares (OLS) may be plagued by bias and inconsistency stemming from the simultaneity of health and income,[9] and thus the inputs to health that may depend on income. The easiest remedy is to use instrumental variables (IV). Pritchett and Summers (1996) identify several relatively strong instruments for aggregate income in their study of the effects of income on infant mortality and life expectancy in a wide macroeconomic panel. These instruments include the terms of trade, the aggregate investment ratio, and a measure of real currency overvaluation relative to the U.S. dollar. To this set I add the nominal effective exchange rate, which I find has independent explanatory power for income. The only instrument I have found for aggregate health care spending is a measure of relative health care prices, constructed as the ratio of a health care price index to the CPI, which I include when I instrument for health spending.[10]

Results

I begin with parsimonious modeling of (6), presenting OLS and IV results alongside one another to aid in interpreting the results. In the first two

in first differences, remain large and significant regardless of which regressors are included in the model. Most other regressors have insignificant effects on e_0.

[9]Unobserved heterogeneity and measurement error may also produce bias and inconsistency. By examining first differences, I have removed sources of unobserved heterogeneity that are fixed over time. Measurement error is a more serious problem that is difficult to address in aggregate studies without many suitable instruments.

[10]As mentioned in note 6, however, price indexes of medical care currently do not measure inflation particularly well, because they do not adequately account for quality improvements. Official indexes typically price health care outputs by pricing inputs, which neglects the effects of productivity improvements. To the extent this may be standard across all countries, of course, relative medical prices could still be effective instruments.

columns in Table 1, I explore a simple model of population health in which the change in life expectancy is a function of the change in log real income per capita, the change in years of education per capita, a constant, and country dummies. In the first column, I present estimates obtained by OLS, and in the second column I show IV estimates after instrumenting for income.[11] Sweden is the omitted country in each regression; the constant term thus represents the average increase in e_0 in Sweden during the sample due to factors other than trends in the regressors. The country dummies measure faster or slower average growth in country-specific e_0 relative to Sweden.

The coefficients on log income and education in the first two columns are positive and thus consistent with theory, but they are imprecise and not significantly different from zero. The coefficient on log income rises substantially when income is instrumented, which is consistent with the presence of measurement error in income, but its standard error rises as well. The first-stage F statistic in the IV specification indicates strong instruments, and the Sargan statistic testing overidentification fails to reject exogeneity of the instruments and correct model specification. The two coefficients on log income suggest that 1 percent faster income growth is associated with a small increase in e_0 of between 0.00013 and 0.00735. The larger number is roughly comparable with the results of Pritchett and Summers (1996), who find a 1 percent increase in income associated with a 0.008–0.0125 year increase in e_0 in a wide panel of rich and poor countries, although their results are also insignificant. The effect of education remains around 0.035 years of life per additional year of schooling in both columns.

Insignificance of the income and education coefficients points toward the central finding: these regressions draw their power from the constant term and the country dummies, the latter of which highlight significant unexplained differences between countries in the rates of increase of e_0. Given trends in income and education, Japan has significantly outperformed the baseline by more than 0.15 year per year. In other words, Japan's baseline growth has been roughly twice that of Sweden's during the sample. Italy and Germany are also high achievers in life expectancy, while Denmark, the Netherlands, and Norway lag behind, albeit insignificantly relative to Sweden. Once differences in income and education are taken into account, the

[11] I estimate all specifications using STATA's "ivreg2" with autocorrelation-consistent standard errors. Instrumental variables estimates use a two-step efficient GMM algorithm. Details are available at http://ideas.repec.org/c/boc/bocode/s425401.html or within STATA by typing "help ivreg2."

U.S. and UK do not appear to be underachievers, which contravenes the prevailing wisdom. The country dummies are jointly significantly different from zero, as shown in the fifth and sixth rows from the bottom of the table, and many are significantly different from each other as well. Their sum averages about 0.04, which, when added to the average constant term, helps accounts for most of the roughly 0.2 year average annual increase in e_0 that we have witnessed among this group since 1960.

Columns 3 and 4 in Table 1 present OLS and IV results after I add the Gini index of income inequality from the Deininger and Squire (1996) dataset to the set of regressors. Its effect is far from clear, since it changes sign between columns and is insignificant in both. The effect of income swings negative when the Gini is included in the OLS specification, but it returns to a positive value when income is instrumented in column 4. One possible interpretation of this is that income inequality may increase with income but also reduce health, which then reduces income. Including income inequality doubles the estimated impact of education on e_0, but it remains insignificant. Little else changes when income inequality is added: all coefficients remain jointly significant, the instruments for income are still valid, and the country dummies remain largely unchanged. Japan is still a significant outlier, as is Germany in the IV results shown in column 4. The dummy on Italy is significant at the 10 percent level in columns 2–4.

These initial results prompt several questions. First, how important is Japan's role in driving these results? It is widely recognized that postwar trends in Japanese life expectancy have overshadowed those in other countries, so it is important to determine whether the emerging puzzle merely reflects Japanese exceptionalism. In columns 1 and 2 of Table 2, I drop Japan from the sample and repeat the OLS and IV estimation. Overall, results are little changed qualitatively, but the model fit has worsened. We cannot reject the hypotheses that all coefficients are equal to zero at the 5 percent level in either regression. But taken in isolation, the country dummies are jointly significant at the 6 percent level in column 1, and once we instrument for income in column 2, the dummy on Germany becomes individually significant. Again, the Italy dummy remains significant at the 10 percent level in both columns. Overall, Japan's role in the puzzle does not appear to be critical.

A second question is whether these results are robust to the choice of income inequality dataset. The Luxembourg Income Study (LIS) Microdatabase (2005) provides data on income inequality considered to be of higher quality than the data collected by Deininger and Squire (1996). Unfortunately, the LIS covers fewer years in the past, and it does not include Japan, although it does cover Austria and Switzerland.[12] The net result is that sample sizes are considerably smaller with the LIS data, which naturally worsens inference. This is apparent in columns 3 and 4 of Table 2, where I switch to the LIS and reestimate the simple model. The signs on income and education are negative in both columns, which is inconsistent with theory. The LIS Gini is negatively signed in both columns and larger, but it is also noisier and thus still insignificant. We cannot reject the F-test on all regression coefficients equal to zero in either column. Taken alone, the country dummies and the constant term are less insignificant. Although it shrinks in magnitude, the German dummy remains significant at the 10 percent level, and the dummies are jointly significant at the 8 percent level. The choice of inequality dataset also does not appear to be crucial, although it affects precision considerably.

A third, much broader question is whether these results are to be expected given the sometimes ambiguous relationship between income and adult health. Pritchett and Summers (1996) cite motor vehicle accidents and the consumption of tobacco, alcohol, and unhealthy foods as adult mortality risks that may actually rise with income. In order to control for external sources of mortality such as accidents, homicides, and suicides, I use data on causes of death taken from the World Health Organization Mortality Database (2004) to scale down mortality rates from the HMD and produce a hypothetical e_0' for all non-external causes of death. Columns 5 and 6 of Table 2 show the results of modeling e_0' using log income, education, income inequality from the Deininger-Squire dataset, and country dummies. Removing external causes strengthens the association between income and life expectancy considerably. It even becomes significant at the 5 percent level in the IV regression in column 6, which associates an increase of 0.014 year in e_0' with a one percent increase in income, still small but about twice that found in column 2 of Table 1. But the rest of the results are similar to those in columns 3 and 4 of Table 1. Education and income inequality are still insignificant, and country dummies on Germany, Italy, and Japan are all significantly different from zero, and they are large. Simply removing

[12]The LIS is also different in that its pretabulated Gini coefficients measure income after taxes and transfers as opposed to before-tax income inequality. Before-tax inequality may be preferable for exploring psychosocial pathways, while after-tax income is probably more important for the functional relationship between purchasing power and health. It is unclear which measure should be preferable ex ante.

external causes does not resolve the puzzle.[13]

Next, I explore how more direct inputs to health, such as purchases of health care goods and services, smoking, alcohol use, and diet, may help explain trends in e_0. I begin by combining shares of GDP spent on health by funding source from the OECD Health Database with per capita income data from the Penn World Table, producing measures of real public and private spending per capita on health.[14] Columns 1 and 2 of Table 3 display the results of including these covariates in OLS and IV estimation of (6). Their coefficients are negative and very imprecise in both columns. Even when the new variables are instrumented in column 2, using relative inflation in the health price index along with the other instruments for income, they are paradoxically estimated to reduce population health, albeit insignificantly. Weak instruments do not appear to be the issue, although private health spending is not as well described by the instrument set as public health and income are. Meanwhile, the country dummies and constant term maintain their signs, levels, and significance.

In columns 3–6 of Table 3, I further expand the set of regressors to include measures of cigarette smoking, alcohol use, and diet. In the case of the latter two variables, research suggests there may be optimal healthy intake levels, rather than monotonic relationships between them and health. I therefore include squared terms in the regressions.[15] In each of the columns, cigarette smoking has the negative impact on e_0 that we would expect, but its effect is imprecise and relatively small, fluctuating between about -0.025 and -0.1 year of e_0 per thousand cigarettes smoked per person per year.[16] Alcohol

[13]I also explored whether restricting attention to female e_0 might change the results. Males typically engage in riskier behavior, and they also suffer from higher incidence of heart disease than females. I found that focusing on females alone produced results that were very similar to those I discovered after removing external causes of death. The impact of income became sharper, education and income inequality still had little impact, and country dummies actually increased in significance.

[14]These should not be confused with measures of real quantities of health goods and services. Producing such data would require constructing accurate price indexes that are comparable across time and space, a major undertaking that is the subject of ongoing research (Triplett, 2002).

[15]Results are qualitatively similar if I omit second-order effects.

[16]Fellows et al. (2002) find that U.S. smokers lose about 14 years of life on average due to smoking. Given that $e_0 = 77$, about 2,000 cigarettes are consumed per person per year, and about 20 percent of the U.S. population smokes daily, a differential in group-e_0 of 14 years would imply an average effect of thousands of cigarettes around -1.5, more than ten times larger than what I find. Of course, it is conceivable that the marginal effect of

consumption has less of a clear impact on health. Its sample mean is 0.9 liters per capita per month, at which the marginal impact of alcohol on health is always negative across columns 3–6, averaging -0.6. The optimal level of alcohol consumption is unstable, as shown by the shifting signs. The dietary intake variables have similarly unstable, insignificant effects and do not merit additional discussion. As shown in the second half of the table, F-tests on the significance of the regression coefficients become harder to reject when these regressors are included, even though the constant term and country dummies remain individually significant.

In Table 4, I drop income, health spending, and the Gini from the equation and look for explanatory power from three new variables involving the supply of health care. OECD Health provides data on hospital beds, health sector employment, and pharmaceutical employment, and I express these relative to population and include them in the model along with education, smoking, alcohol, diet, and the country dummies. I report OLS estimates alone because strong instruments are not readily available for these new variables; the previous instrument set provides extremely poor fits. It also bears emphasizing that we do not have any measures of productivity to complement measures of labor and capital involved in health care production, and that omission appears to be fairly important.

The results across all three columns conform to what is now a familiar pattern: the continuous regressors have insignificant effects on e_0, while the constant and the time dummies remain important. This holds regardless of which production-side variables I include, as I show by sequentially dropping them across columns. More hospital beds are actually associated with less health, which may initially seem paradoxical. It is widely known that technological change in health care, a key omitted variable here, has favored outpatient over inpatient care. We actually see declines in beds per capita in most countries during the sample period, even though e_0 is rising. Increases in health sector employment are only weakly associated with increases in e_0, while pharmaceutical employment is oddly associated with poorer health. This may reflect the fact that many of the most rapid increases in pharmaceutical employment in the sample occurred in Denmark, an underperformer in e_0. Education, smoking, alcohol, and diet variables remain insignificant and sometimes fluctuate in sign.[17]

cigarettes, which is what the regression recovers, is far smaller than the average effect at current levels of consumption.

[17]The effect of alcohol is convoluted; it is U-shaped rather than inverted-U in columns

Discussion

In this paper, I have demonstrated that patterns of mortality decline among industrialized countries since 1960 cannot be explained by any combination of observable trends in economic growth, education, income inequality, the provision of health care, smoking, drinking, and diet. Although there is much variation both in levels and trends in these inputs to health across advanced countries, they cannot explain divergent trends in life expectancy at birth between countries.

This result is puzzling because it is incongruous with other key facts. There has been much convergence in incomes among these countries since the Second World War, and much of that convergence is typically attributed to technological convergence. There has also been much convergence in life expectancy over the same period, so much so that one scholar has remarked that "this set of the large, established developed countries is behaving increasingly as if it had a single mortality pattern" (White, 2002). Why then should the joint distributions of income and life expectancy not be converging, even though the marginal distributions are? We do not yet have a good answer for this, which is troubling because it highlights a gap in our knowledge regarding the sources of differential mortality, a fundamental inequality in human well-being.

It is true that we do not have many good measures of the key determinant of intertemporal change in life spans: health technology. But given convergence in general production technology among advanced countries, it would be puzzling if simultaneously there were also divergence in health technology among them. The measures of health technology that exist, such as Lichtenberg's (2003) proprietary panel data on drug approvals, in fact do not register differential rates of growth across countries over time. But what do we mean by "technology?" Do we strictly mean availability, or are we also referring to the actual utilization of techniques?

1 and 3, and in column 2 its optimum occurs with negative consumption. Coefficients on the diet variables are still insignificant, but there is somewhat more agreement across specifications on the optimal intake levels. The estimated optimal level of caloric intake averages nearly 4,000 kilocalories per person per day, which is high relative to the suggested range in the USDA Dietary Guidelines for 2005, 1,000 to 2,800 depending on age and sex. Estimates suggest fat consumption is optimal at a staggering 150 grams per day, which is below French and Danish average intakes but roughly three times the recommended daily U.S. level. Optimal protein intake is around 80 grams per day, which is currently below consumption levels in every nation in the sample.

The distinction may be very important for health while it apparently remains unimportant for consumption goods, because health production differs in fundamental ways from the production of consumption goods, even though both are complementary goods from the perspective of the individual. It is well known that due to the structure of delivery markets and of health insurance, pricing signals do not function as well in health care markets as in others. This may impede the actual implementation of new techniques when they become available. By and large, firms that do not advance to the technology frontier lose profitability and either change their behavior or cease to exist. Individuals who do not utilize new health technologies may not feel the effects of their decisions for many years. It is clear that rather than measure the availability of health technologies, we should be trying to measure utilization on a per capita basis across countries.

Identifying inequality in utilization of health technologies is another closely related goal. It has become increasingly clear in recent years that income inequality, the most common aggregate measure, is of extremely limited importance in explaining population health, as described in a review by Lynch et al. (2004). Edwards and Tuljapurkar (2005) show that income inequality does not explain variance in the adult age at death, a key indicator of aggregate health inequality that has behaved very differently across advanced countries since 1960. In order to inform future research into international mortality differentials, we need to understand inequalities in the inputs to health, such as access to technology, knowledge, and care, that are producing the aggregate health inequalities that we observe. Without a doubt, they will be important in explaining average health outcomes as well.

Several other issues deserve mention. In this paper, I have made no attempt to test for the presence of lagged effects on health of past behaviors and circumstances, since it is unlikely that aggregate data could ever adequately test for such influences. While lagged effects may have a more pronounced impact on population health than is widely appreciated, I leave such inquiry for future efforts with more suitable data. Second, aside from smoking behavior, I have limited information on how behaviors and preferences may differ across countries. It is conceivable that there could be fundamental differences between societies in preferences like risk aversion, intertemporal substitution, and altruism that explain different rates of growth in life span and consumption. Direct measures of such preferences do not exist, and attempts to recover estimates using aggregate models typically cannot identify significant differences between countries. Third, results from a growing body of research suggest that different genetic characteristics of individuals are important for longevity. Whether these genes vary systematically by national origin, or whether genes could produce differential growth rather than level effects in longevity, remains to be seen.

While it remains unclear exactly what other factors may be responsible for growing inequalities in life expectancy among advanced nations, there are clear directions for future research. Much work remains to be done in identifying the sources of widening mortality differentials in a systematic way across countries.

Appendix

The data

Aggregate mortality data are available for industrialized countries at annual frequencies and in single years of age from the Human Mortality Database (2005). These data are based on highly reliable sources: officially enumerated populations and death records. I restrict my analysis to 14 countries in the period since 1960: Austria, Canada, Switzerland, Denmark, Finland, France, the UK, Germany, Italy, Japan, the Netherlands, Norway, Sweden, and the United States. Data for the UK covers England and Wales only. German data covers West Germany only up to 1992. I use life expectancy at birth for both sexes combined, e_0, as my primary indicator of population health.

Real income aggregates are provided by the Penn World Table 6.1 (Heston, Summers and Aten, 2002).[18] There are two different income inequality databases: the Luxembourg Income Study (LIS) Microdatabase (2003), and the Deininger and Squire (1996) dataset. Both have serious drawbacks. The LIS does not include Japan, it covers a shorter time span, and measurements are infrequent. Although the Deininger-Squire data has better coverage across time and space, it is thought to suffer from more measurement error.

I obtain average years of education among the population aged 25 years and older at 5-year frequencies since 1960 from Barro and Lee (2000). Measures of health spending by source, hospital beds, health sector employment, pharmaceutical employment, price indexes, alcohol consumption, and smoking are available in the OECD Health Data (2004). Additional smoking data

[18] I construct real GDP per capita for West Germany by rescaling data from version 5.6.

are maintained by the Foreign Agricultural Service of the U.S. Department of Agriculture. The UN's FAOSTAT database provides dietary intake data.

Pritchett and Summers (1996) identify several relatively strong instruments for aggregate income in their study of the effects of income on infant mortality and life expectancy in a wide macroeconomic panel. These include the terms of trade, which I construct using OECD Economic Outlook data as the ratio of each country's export price index to its import price index; the aggregate investment ratio, available from the Penn World Table; and a measure of real currency overvaluation relative to the U.S. dollar, obtained from the World Bank's Global Development Network Growth Database. The OECD Health database includes consumer price indexes for health goods and services, which I augment using national sources for Norway and Japan, in addition to price indexes for all consumption goods. The ratio of the health CPI to the total CPI is a measure of relative health care prices and thus a determinant and potential instrument for the demand for health care.

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Table 1: Income, education, and income inequality fail to explain differential trends in life expectancy by country

dependent variable: Δe_0	1 OLS	2 IV	3 OLS	4 IV
Δ log income	0.013	0.735	−0.179	0.609
	(0.389)	(0.582)	(0.467)	(0.692)
Δ education	0.033	0.036	0.063	0.077
	(0.090)	(0.091)	(0.110)	(0.110)
Δ income Gini			−0.333	0.124
			(1.327)	(1.327)
Austria	0.076*	0.071		
Canada	0.039	0.038	0.041	0.037
Switzerland	0.048	0.053		
Denmark	−0.052	−0.053	−0.069	−0.067
Finland	0.050	0.045	0.071	0.064
France	0.050	0.048	0.052	0.047
UK	0.003	0.003	0.018	0.014
Germany	0.065	0.109**	0.071	0.138**
Italy	0.091**	0.081*	0.091*	0.083*
Japan	0.167**	0.151**	0.211**	0.185**
Netherlands	−0.047	−0.045	−0.004	−0.005
Norway	−0.044	−0.051	−0.035	−0.044
USA	0.012	0.009	0.014	0.007
constant	0.163**	0.147**	0.162**	0.148**
N	535	520	358	349
F on all coef	3.27	3.43	2.9	3.26
prob > F	0.00	0.00	0.00	0.00
F on countries	49.08	46.03	40.38	38.61
prob > F	0.00	0.00	0.00	0.00
F, first stage		127.42		87.1
prob > F		0.00		0.00
Sargan overid		1.81		0.64
prob > χ^2		0.61		0.89

(Notes on next page)

Notes: The dependent variable in all regressions is the annual change in life expectancy at birth, e_0, for both sexes combined. Log income and education are measured per person, and are first-differenced along with the Gini. Country names refer to 0/1 dummies showing additional average annual increases in e_0 added to the constant term. The excluded country is Sweden. Standard errors for the continuous regressors are in parentheses. Two asterisks denote 5% significance; one denotes 10%. In columns 2 and 4, I instrument for log income using the investment ratio, the terms of trade, the nominal effective exchange rate, and a measure of real currency overvaluation. Columns 3 and 4 use Gini's from the Deininger and Squire (1996) database, which does not cover Austria or Switzerland. All equations are estimated using STATA's "ivreg2" with autocorrelation-consistent standard errors; IV estimates use two-step efficient GMM. The F-statistics test all second-stage coefficients equal to zero all country dummies equal to zero, and all coefficients in the first stage equal to zero. The Sargan statistic tests overidentification; a high p-value is a failure to reject exogeneity of the instruments and correct specification. See the appendix for data sources.

Table 2: Neither dropping Japan, using income inequality from the high-quality LIS, nor removing external causes helps explain life expectancy

dependent variable: Δe_0	1 OLS	2 IV	3 OLS	4 IV	5 OLS	6 IV
Δ log income	−0.246	0.779	−0.225	−0.312	0.514	1.418**
	(0.498)	(0.731)	(0.483)	(0.643)	(0.482)	(0.714)
Δ education	0.078	0.084	−0.004	−0.004	0.088	0.108
	(0.110)	(0.110)	(0.116)	(0.116)	(0.110)	(0.109)
Δ income Gini	−0.843	−0.396	−4.607	−4.549	−0.366	0.096
	(1.374)	(1.377)	(3.192)	(3.202)	(1.372)	(1.365)
Austria			0.089	0.089		
Canada	0.043	0.037	0.017	0.018	0.041	0.035
Switzerland			−0.018	−0.017		
Denmark	−0.067	−0.063	−0.065	−0.065	−0.057	−0.055
Finland	0.072	0.063	0.039	0.039	0.083*	0.075*
France	0.053	0.044	0.047	0.047	0.066	0.058
UK	0.022	0.017	0.017	0.017	0.026	0.020
Germany	0.075	0.139**	0.084*	0.084*	0.070	0.116**
Italy	0.092*	0.084*	0.065	0.065	0.100**	0.092**
Japan	X	X			0.191**	0.161**
Netherlands	−0.001	−0.002	−0.078	−0.077	−0.008	−0.010
Norway	−0.035	−0.047	−0.035	−0.034	−0.040	−0.054
USA	0.017	0.009	0.007	0.008	0.024	0.015
constant	0.160**	0.143**	0.199**	0.200**	0.133**	0.117**
N	330	321	215	214	346	338
F on all coef	1.34	1.68	1.34	1.33	3.38	3.77
prob > F	0.19	0.06	0.18	0.18	0.00	0.00
F on countries	17.45	21.37	19.66	19.48	40.58	0.00
prob > F	0.06	0.02	0.07	0.08	0.00	0.00
F, first stage		82.89		83.07		87.56
prob > F		0.00		0.00		0.00
Sargan overid		1.14		2.64		0.45
prob > χ^2		0.77		0.45		0.93
Note	Japan omitted		LIS Gini's		Non-external causes	

(Notes on next page)

Notes: The dependent variable in all regressions is the annual change in life expectancy at birth, e_0, for both sexes combined. Log income and education are measured per person, and are first-differenced along with the Gini. Country names refer to 0/1 dummies showing additional average annual increases in e_0 added to the constant term. The excluded country is Sweden. Standard errors for the continuous regressors are in parentheses. Two asterisks denote 5% significance; one denotes 10%. In columns 2, 4, and 6, I instrument for log income using the investment ratio, the terms of trade, the nominal effective exchange rate, and a measure of real currency overvaluation. Columns 1, 2, 5, and 6 use Gini's from the Deininger and Squire (1996) database, which does not cover Austria or Switzerland. In columns 1 and 2, I drop Japan. In columns 3 and 4, I use Gini's from the Luxembourg Income Study (LIS) Microdatabase (2003), which does not include Japan. In columns 5 and 6, I return to the Deininger-Squire inequality measure but construct Δe_0 for non-external causes (i.e., no accidents, homicides, or suicides) from HMD data combined with cause-of-death data from the World Health Organization Mortality Database (2004). All equations are estimated using STATA's "ivreg2" with autocorrelation-consistent standard errors; IV estimates use two-step efficient GMM. The F-statistics test all second-stage coefficients equal to zero, all country dummies equal to zero, and all coefficients in the first stage equal to zero. The Sargan statistic tests overidentification; a high p-value is a failure to reject exogeneity of the instruments and correct specification. See the appendix for data sources.

Table 3: Including health spending, smoking, alcohol use, and diet variables does not help explain changes in life expectancy

dependent variable: Δe_0	1 OLS	2 IV	3 OLS	4 IV	5 OLS	6 IV
Δ log income	0.160	0.141	−0.271	−0.031		
	(0.487)	(0.888)	(0.556)	(1.379)		
Δ log pub health	−0.371	−0.892	−0.496	−1.023	−0.546**	0.133
	(0.263)	(1.277)	(0.331)	(2.318)	(0.276)	(0.961)
Δ log pvt health	−0.038	−0.787	−0.053	−1.466	−0.023	−0.499
	(0.088)	(1.048)	(0.097)	(2.198)	(0.091)	(0.895)
Δ education	0.040	0.016	0.013	0.007	−0.022	0.076
	(0.107)	(0.136)	(0.114)	(0.165)	(0.096)	(0.117)
Δ income Gini	−0.113	−0.035	0.073	0.382		
	(1.322)	(1.598)	(1.317)	(2.091)		
Δ cigarettes			−0.065	−0.074	−0.028	−0.093
			(0.111)	(0.139)	(0.080)	(0.108)
Δ alcohol			−0.130	−2.174	0.290	−1.362
			(1.601)	(3.225)	(1.427)	(2.044)
Δ alcohol^2			−0.269	0.495	−0.239	0.460
			(0.721)	(1.316)	(0.643)	(0.899)
Δ calories			0.222	2.189	0.551	0.871
			(4.844)	(7.017)	(4.028)	(5.549)
Δ calories^2			0.009	−0.304	−0.051	−0.052
			(0.755)	(1.092)	(0.616)	(0.855)
Δ fat			0.215	0.041	0.400	0.172
			(0.319)	(0.462)	(0.274)	(0.365)
Δ fat^2			−0.008	−0.000	−0.014	−0.007
			(0.011)	(0.017)	(0.010)	(0.013)
Δ protein			0.243	−1.166	0.420	−0.155
			(1.060)	(2.241)	(0.854)	(1.136)
Δ protein^2			−0.013	0.058	−0.024	0.005
			(0.054)	(0.112)	(0.044)	(0.057)
Austria					0.087*	0.097
Canada	0.044	0.060	0.054	0.074	0.056	0.052
Switzerland					0.052	
Denmark	−0.079	−0.079	−0.073	−0.060	−0.087*	−0.065
Finland	0.070	0.087	0.032	0.067	0.033	0.052
France	0.059	0.090	0.057	0.093	0.067	0.083
UK	0.015	0.026	0.013	0.067	0.008	0.029
Germany	0.143**	0.168**	0.150**	0.199*	0.113**	0.126**
Italy	0.082*	0.118*	0.076	0.142	0.078*	0.132*
Japan	0.216**	0.270**	0.182**	0.251**	0.126**	0.140**
Netherlands	−0.008	−0.008	−0.012	−0.013	0.006	0.012
Norway	−0.027	0.073	0.001	0.139	0.005	0.029

(continued next page)

Table 3: *(continued)*

dependent variable: Δe_0	1 OLS	2 IV	3 OLS	4 IV	5 OLS	6 IV
USA	0.023	0.062	0.038	0.092	0.039	0.030
constant	0.173**	0.200**	0.181**	0.208**	0.180**	0.155**
N	349	319	270	255	358	306
F on all coef	3.05	2.22	1.57	0.94	1.64	1.34
prob > F	0.00	0.00	0.05	0.55	0.03	0.14
F on countries	48.10	29.86	27.26	15.34	28.27	22.03
prob > F	0.00	0.00	0.00	0.17	0.01	0.04
F, income 1st		83.43		78.75		
prob > F		0.00		0.00		
F, pub health 1st		6.18		7.31		7.87
prob > F		0.00		0.00		0.00
F, pvt health 1st		1.74		1.38		1.53
prob > F		0.13		0.23		0.18
Sargan overid		0.05		0.62		1.17
prob > χ^2		0.97		0.73		0.76

Notes: The dependent variable in all regressions is the annual change in life expectancy at birth, e_0, for both sexes combined. Continuous regressors are measured per person and first-differenced. Country names refer to 0/1 dummies showing additional average annual increases in e_0 added to the constant term. The excluded country is Sweden. Standard errors for the continuous regressors are in parentheses. The cigarettes variable measures thousands of cigarettes smoked per person per year; alcohol measures liters per capita per month; calories are in thousands of kilocalories per person per day; fat and protein measure daily intakes in 10's of grams. Two asterisks denote 5% significance; one denotes 10%. In columns 2, 4, and 6, I instrument for income and health spending using relative health care price inflation, the investment ratio, the terms of trade, the nominal effective exchange rate, and a measure of real currency overvaluation. All equations are estimated using STATA's "ivreg2" with autocorrelation-consistent standard errors; IV estimates use two-step efficient GMM. The F-statistics test all second-stage coefficients equal to zero, all country dummies equal to zero, and all coefficients in the first stage equal to zero. The Sargan statistic tests overidentification; a high p-value is a failure to reject exogeneity of the instruments and correct specification. See the appendix for data sources.

Table 4: Including health spending, smoking, alcohol use, and diet variables does not help explain changes in life expectancy

dependent variable: Δe_0	1 OLS	2 OLS	3 OLS
Δ beds	−0.033	−0.043	
	(0.041)	(0.039)	
Δ health sector employment	0.010	0.012	
	(0.008)	(0.008)	
Δ pharmaceutical employment	−0.014		
	(0.197)		
Δ education	0.026	0.043	−0.039
	(0.122)	(0.113)	(0.092)
Δ cigarettes	−0.009	0.001	−0.024
	(0.105)	(0.103)	(0.080)
Δ alcohol	−0.747	−0.315	−0.733
	(1.574)	(1.450)	(1.280)
Δ alcohol^2	0.186	−0.115	0.142
	(0.761)	(0.686)	(0.588)
Δ calories	0.906	0.625	1.042
	(4.505)	(4.333)	(3.948)
Δ calories^2	−0.134	−0.074	−0.124
	(0.694)	(0.666)	(0.604)
Δ fat	0.217	0.327	0.315
	(0.301)	(0.273)	(0.269)
Δ fat^2	−0.007	−0.011	−0.011
	(0.010)	(0.010)	(0.009)
Δ protein	0.133	0.311	0.220
	(0.934)	(0.910)	(0.818)
Δ protein^2	−0.008	−0.019	−0.014
	(0.048)	(0.047)	(0.042)
Austria			0.073
Canada	0.069	0.066	0.047
Switzerland	0.016	0.008	0.042
Denmark	−0.054	−0.058	−0.070
Finland	0.032	0.028	0.036
France	0.101*	0.084	0.059
UK	0.054	0.017	0.006
Germany	0.116**	0.105**	0.052
Italy	0.095*	0.082*	0.070
Japan	0.156**	0.141**	0.116**
Netherlands	0.022	0.020	−0.023
Norway	−0.015	−0.019	−0.005
USA	0.051	0.034	0.020
constant	0.141**	0.136**	0.168**

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Table 4: *(continued)*

dependent variable: Δe_0	1 OLS	2 OLS	3 OLS
N	270	304	373
F on all coef	1.42	1.77	1.61
prob > F	0.09	0.02	0.04
F on countries	25.12	25.43	21.27
prob > F	0.01	0.01	0.07

Notes: The dependent variable in all regressions is the annual change in life expectancy at birth, e_0, for both sexes combined. Continuous regressors are measured per person and first-differenced. Country names refer to 0/1 dummies showing additional average annual increases in e_0 added to the constant term. The excluded country is Sweden. Standard errors for the continuous regressors are in parentheses. The beds variable measures the number of in-patient hospital beds per 1,000 people; health sector employment and pharmaceutical employment are people employed in the sector per 1,000 people. The cigarettes variable measures thousands of cigarettes smoked per person per year; alcohol measures liters per capita per month; calories are in thousands of kilocalories per person per day; fat and protein measure daily intakes in 10's of grams. Two asterisks denote 5% significance; one denotes 10%. All equations are estimated using STATA's "ivreg2" with autocorrelation-consistent standard errors. The F-statistics test all second-stage coefficients equal to zero and all country dummies equal to zero. See the appendix for data sources.