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The economic burden of chronic diseases: Estimates and projections for China, Japan, and South Korea☆,☆☆

David E. Bloom[a], Simiao Chen[a], Michael Kuhn[b], Mark E. McGovern[c,d], Les Oxley[e], Klaus Prettner[f]

[a] Department of Global Health and Population, Harvard T.H. Chan School of Public Health, United States
[b] Wittgenstein Centre (IIASA, VID/ÖAW, WU), Vienna Institute of Demography, Austria
[c] CHARMS - Centre for Health Research at the Management School, Queen's University Belfast, United Kingdom
[d] UKCRC Centre of Excellence for Public Health (Northern Ireland), United Kingdom
[e] Waikato Management School, The University of Waikato, New Zealand
[f] University of Hohenheim, Institute of Economics, Germany

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ABSTRACT

We propose a novel framework to analyze the macroeconomic impact of non-communicable diseases. We incorporate measures of disease prevalence into a human capital augmented production function, which enables us to determine the economic burden of chronic health conditions in terms of foregone gross domestic product (GDP). Unlike earlier frameworks, this approach allows us to account for i) variations in human capital for workers in different age groups, ii) mortality and morbidity effects of non-communicable diseases, and iii) the treatment costs of diseases. We apply our methodology to China, Japan, and South Korea, and estimate the economic burden of chronic conditions in five domains (cardiovascular diseases, cancer, chronic respiratory diseases, diabetes, and mental health conditions). Overall, total losses associated with these diseases over the period 2010–2030 are (measured in real USD with the base year 2010) estimated to be $7.7 trillion for China, $3.5 trillion for Japan, and $1 trillion for South Korea.

1. Introduction

Globally, non-communicable diseases (NCDs) are responsible for 65% of all deaths (Lozano et al., 2011) and 54% of all healthy life years lost as measured by DALYs (disability-adjusted life years) (Murray et al., 2013). Apart from the enormous pain and suffering that these conditions impose, the global economic burden of non-communicable diseases has been estimated to be in the region of $47 trillion from 2010 through 2030 (measured in ppp-adjusted international dollars with the base year being 2010, or 75% of global GDP in 2010; see Bloom et al., 2012). Moreover, the prevalence of chronic conditions, specifically NCDs such as cardiovascular diseases, cancer, chronic respiratory diseases, diabetes, and mental health conditions, will rise substantially over the coming decades (Kearney et al., 2005).

This phenomenon is likely to affect not only developed countries but also low- and middle-income countries as a result of changes in modifiable risk factors (such as smoking, dietary, and exercise patterns) and non-modifiable risk factors (such as population ageing). One important factor driving chronic disease prevalence worldwide is the shift of lifestyle patterns toward more sedentary occupations and less healthy diets. Urbanization has many economic benefits in terms of returns to agglomeration, specialization, and efficiency, but it can also affect population health negatively through mechanisms such as diffusion of risky behaviour and exposure to pollution. One important difference in risk factor trajectories between low- and middle-income countries and high-income countries is the divergence in smoking patterns. While cigarette and tobacco consumption has been falling in many high-income countries, it has been rising in India and China. Given that tobacco consumption is the most important risk factor for many non-communicable diseases, this increase is likely to raise their prevalence

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in those countries. Another difference between developed and developing countries is that the former have been quite successful at minimizing the risk of death associated with communicable diseases, whereas communicable diseases remain a major contributor to mortality in low-income countries. This implies that low-income countries often face the double burden of non-communicable and communicable diseases.

In developed countries, population ageing is an inexorable consequence of changing fertility and mortality patterns. Many high-income countries already face rapid demographic change, and because chronic conditions tend to increase with age, the proportion of their populations affected by non-communicable diseases will rise. Likewise, many emerging economies are either already experiencing population ageing or will do so in the near future. Particularly interesting cases for studying the effects of ageing-related increases in non-communicable disease prevalence are Japan, because it has the largest share of older people globally, and China and South Korea, because they are experiencing very rapid population ageing. The main goals of this paper are to estimate and project the economic burden of cardiovascular diseases, cancer, chronic respiratory diseases, diabetes, and mental health conditions for these three countries until 2030 and to compare the corresponding challenges that these countries face.

Through several pathways, the disease burden affects economic outcomes in general and economic growth in particular.[1] First, chronic conditions reduce the supply of labour through mortality, early retirement (Dwyer and Mitchell, 1999; Lindeboom and Kerkhofs, 2009; Jones et al., 2010), and reduced productivity (López-Casasnovas et al., 2005; Jäckle and Himmler, 2010). In addition, individuals may alter their employment behaviour because they anticipate, or fear, the future onset of illness and negative effects of health conditions (McGarry, 2004).[2] Second, current interventions related to NCDs (including medical treatment and prevention) require a substantial amount of resources, part of which could instead be used for other productive activities. Therefore, NCDs reduce the net availability of government funds and impede the accumulation of physical capital by, for example, diverting investment from important areas such as education and infrastructure. Additionally, reduced productivity and lower labour supply, in tandem with higher private health care costs, will lead to a decline in aggregate income and, therefore, further reduce savings and investment. Third, if the impact of NCDs varies by age, then age group differences in (average) education and experience will impact the aggregate human capital stock. Our model integrates these pathways, as summarized in Fig. 1, into a macroeconomic production framework. Focusing on the impact of NCDs on the supply of labour, human and physical capital, and the resultant implications for GDP growth allows us to arrive at a comprehensive measure of the economic burden of the NCDs that we consider – as indicated by foregone GDP.

The economic impact of health conditions in general, and non-communicable diseases in particular, is of special importance and interest to policymakers. Faced with increases in the prevalence of chronic conditions, governments and other stakeholders may wish to enact policies that are effective at reducing disease incidence and its consequences. Several possible interventions can reduce the prevalence of non-communicable diseases. For example, a series of "best-buy" investments has been proposed because they are cost-effective and easy to implement within the constraints of low- and middle-income countries. These policies include increasing taxes on alcohol and tobacco sales,

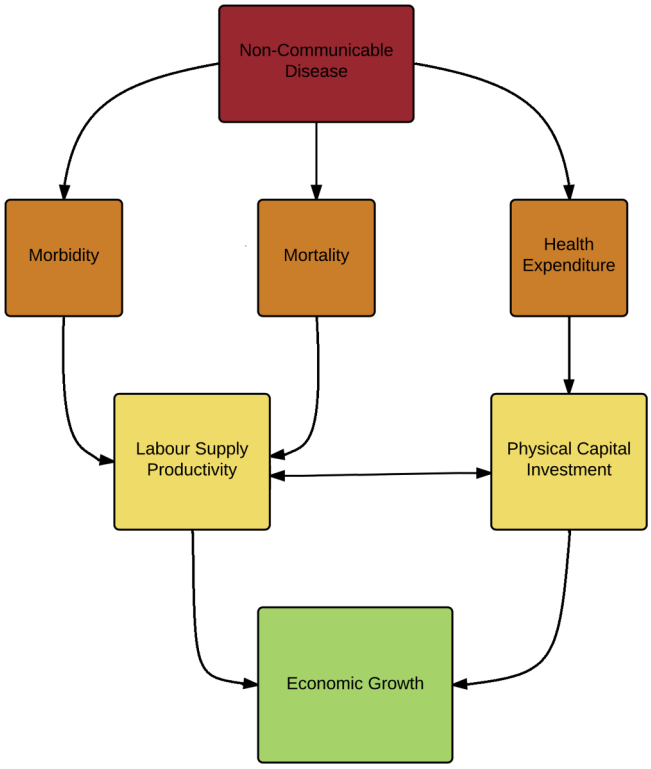

Fig. 1. Summary of pathways from NCDs to economic growth.

reducing salt intake in food, and replacing trans fats with poly-unsaturated fats (Bloom et al., 2011). However, establishing whether particular programs are worthy of investment can be difficult without a thorough assessment of the economic benefits of these interventions.

Approaches to estimating the economic effects of health conditions include the cost of illness method, where the direct and indirect costs associated with a disease are calculated; the value of a statistical life (VSL) approach, where costs are inferred from willingness to pay studies or observed avoidance behaviour for risky occupations or scenarios; econometric estimates taken from cross-country growth regressions; and macroeconomic models (such as a production function-based approach or a general-equilibrium framework), where output trajectories for different scenarios are simulated. Each approach has advantages and disadvantages. In our paper, we aim to account for the aggregate effects on output when estimating the full economic impact of non-communicable diseases. Therefore, we adopt a macroeconomic approach that incorporates disease prevalence into a human capital augmented production function. In this way, we can model the effects of chronic conditions on aggregate effective labour supply and on capital accumulation in a flexible framework that can be used to characterize an extensive set of pathways through which health affects the economy.[3] In contrast to many of the individual-level studies on the economic burden of disease, our macroeconomic approach directly accounts for the salient substitution processes between labour, human capital, and physical capital, as well as the implied changes in factor productivity.

Our main contribution is to modify and extend the model that Abegunde and Stanciole (2006) first used to examine the impact of non-communicable diseases on economic growth. The original formulation of the basic projection tool named EPIC (or Projecting the Economic

[1] For an overview on the effects of health on economic growth and the channels that matter in this context, see Bloom et al. (forthcoming).

[2] For a theoretical analysis of the interrelationship between health and retirement behaviour, see Bloom et al. (2007), Bloom et al. (2014). Building on this, Prettner and Canning (2014) explore the macroeconomic implications, and Kuhn et al. (2015) study the interaction between health and retirement behaviour.

[3] See Kuhn and Prettner (2016) for an analysis of the impact of health care on economic growth and welfare within a Blanchard-Romer style general equilibrium model, in which they take account both of morbidity and mortality related channels.

Cost of Ill Health) relied on the Solow (1956) framework and was designed by the World Health Organization (WHO).[4] In this paper we propose a novel framework that builds upon the WHO EPIC tool, but additionally considers i) heterogeneous human capital levels of workers in different age groups, ii) that NCDs and health conditions not only lead to mortality but also to morbidity, and iii) the effect of treatment costs on capital accumulation.

While our analysis focuses on NCDs, the framework we develop here is quite general and could easily apply to other health domains, such as communicable diseases, road traffic accidents, and tobacco control. We focus on chronic conditions for several reasons. First, the data requirements to implement the model for the four NCDs that are the focus of the United Nations (cardiovascular diseases, cancer, chronic respiratory diseases, and diabetes) and mental health conditions are already quite substantial. Second, the countries we consider (China, Japan, and South Korea) are either middle- or high-income countries that have made great strides in dealing with communicable diseases. However, NCDs have received less attention from a public health perspective in these countries and, unlike communicable diseases, the prevalence of chronic conditions is expected to rise substantially over the coming decades. Finally, we are interested in assessing the economic impact of population ageing via changes in the health status of the population, and because age is an important non-modifiable risk factor for the NCDs that we consider, we believe that focusing on these conditions is appropriate. Nevertheless, we hope to extend the model to other aspects of health in future research.

The paper is organized as follows. Section 2 compares the four most popular methods used to assess the economic burden of different diseases and discusses their advantages and disadvantages. Section 3 proposes a novel framework that builds upon the WHO EPIC tool, but additionally considers heterogeneous human capital levels of workers in different age groups, the morbidity effect of NCDs, and the effect of treatment costs on capital accumulation. Section 4 implements the model for China, Japan, and South Korea and presents the results for these three countries. Section 5 summarizes and draws conclusions.

2. Comparison of methods to assess the economic burden of diseases

This section describes the main approaches used to quantify the economic impact of health conditions, focusing on the advantages and disadvantages of each framework. We start with the cost of illness (COI) approach, which is an easy-to-understand method that summarizes the burden of a certain disease over a particular time period in a single number. This number is defined as the sum of all personal medical care costs (e.g., inpatient and outpatient hospital costs); personal non-medical care costs (e.g., transportation and relocation expenses); non-personal costs (e.g., for research activities); and loss of income due to absenteeism, early retirement, or premature death. Altogether, the medical costs, the non-medical costs, and the research costs are referred to as “direct costs”, while the loss of income is referred to as an “indirect cost”.[5] The advantage of this method is that the outcome is easily interpreted as the monetary value of the resources that could be saved by avoiding a particular disease. The main drawbacks are that no economic adjustment mechanisms are considered (e.g., the substitution of labour lost due to an illness by capital or other workers) and that COI studies disregard the effect of diseases on physical capital and human capital accumulation (for a general debate on the usefulness of the COI approach see Currie et al., 2000; Rice, 2000; World Health Organization, 2009).

An alternative way to estimate the costs of health conditions is to reconstruct a person’s implicit valuation of his/her own life—the value of a statistical life—by estimating a person’s willingness to accept premia for risky occupations via wage regressions, or by estimating a person’s willingness to pay for the reduction of risks via hedonic price regressions (Viscusi and Aldy, 2003). The monetary value that a person assigns to his/her own life can be inferred from the parameter estimates in these regressions. The main advantage of this approach is that it also delivers a single number that, if multiplied by the number of cases, can be interpreted as the total statistical value of the loss due to an illness. While the COI approach focuses more on the objective costs of an illness, the VSL approach also implicitly covers the costs of pain and suffering via the revealed preferences of the consumers/workers who are studied. Prominent studies by Murphy and Topel (2006) and Lakdawalla et al. (2010) apply the VSL methodology to calculate the value of advances against cardiac disease and cancer. The main drawback is that the VSL approach yields an estimate of the statistical loss due to an illness that strongly depends on the age and the income level of workers. Consequently, the estimates vary widely among different countries. Furthermore, economic adjustment mechanisms are typically not taken into consideration.[6]

Another method to assess the economic costs of an illness is to estimate a cross-country growth regression in the vein of Barro (1991) and Islam (1995), in which the main regressors of interest contain the prevalence of the illness under consideration. From the parameter estimate associated with the prevalence of an illness, its impact on growth can be inferred directly (see Suhrcke and Urban, 2010 for estimates of the negative growth effect of cardiovascular diseases). The advantage of this approach is that, when the regression is appropriately specified, the estimated growth effect is readily apparent from the final result, which already incorporates economic adjustment mechanisms. Consequently, this method overcomes one of the crucial shortcomings of the COI and VSL approaches. However, growth regressions are very data intensive, requiring a wide range of precisely measured control variables for all countries in the sample (see Durlauf et al., 2005; Eberhardt and Teal, 2011; Sala-i-Martin et al., 2004; Sala-i-Martin, 1997 for discussions). Furthermore, the result is an average of the growth effect over all countries included in the regression, which does not account for specific country characteristics and potential heterogeneity in the impact of chronic conditions across countries. Additionally, this approach only allows for an assessment of severe diseases that affect many people (such as cardiovascular diseases). Detecting a significant growth effect for less impactful diseases is difficult given the small sample sizes that typically confront growth regressions (cf. Durlauf et al., 2005). Finally, attempts to deal with reverse causality and omitted variable bias are contentious in the literature (Weil, 2014).

Abegunde and Stanciole, 2006 and the WHO first proposed the EPIC framework, which simulates a Solow (1956) growth model that considers the adverse effects of diseases on physical capital accumulation and labour supply. Bloom et al. (2012), Bloom et al. (2014a), Bloom et al. (2014b) and Bloom et al. (2015) have applied this framework to several developed and less-developed countries. While the EPIC approach accounts for the fact that physical capital or other workers can replace lost labour, and therefore allows for economic adjustment mechanisms, it only considers mortality and not morbidity.[7] Furthermore, it does not accurately account for the cost of treatments or for the

[4] The basic EPIC model has been used to estimate the economic burden of chronic conditions in India, China, Indonesia, and worldwide (cf. Bloom et al., 2012; Bloom et al., 2014a; Bloom et al., 2014b; Bloom et al., 2015). An extended version of the EPIC model has also been applied to Costa Rica, Jamaica, and Peru (cf. Bloom et al., 2018).

[5] Most studies of the costs of NCDs rely on this approach (as an example, see Beaulieu et al., 2009).

[6] See Frankovic et al. (2017) for a theoretical analysis of how the VSL responds to exogenous medical progress in general equilibrium.

[7] While Bloom et al. (2018) extends the EPIC model to incorporate morbidity, it does not account for heterogeneous human capital levels of workers in different age groups.

varying productivity of consecutive age groups of workers (due to differences in their schooling and patterns of experience). Accounting for age-dependent productivity is important because of the relative concentration of chronic conditions among older age groups.

Our contribution focuses on these three shortcomings of the EPIC model and proposes a novel framework that builds upon the Lucas (1988) production function. In so doing, we explicitly allow different age groups of workers to have different education levels and different levels of experience, and we address the lack of a morbidity mechanism by incorporating information on disease morbidity, as measured by DALYs reported by the Institute for Health Metrics and Evaluation (2013). Furthermore, we account for the treatment costs of diseases.

The production function-based framework we use also has some limitations. First, it is not a general equilibrium model in the sense that all decisions are microfounded. For example, individuals who live longer because the prevalence of a disease is reduced might invest more in education or they might save more. While implementing a general equilibrium structure would be highly complex and would require other restrictive assumptions to be tractable, disregarding the mentioned general equilibrium repercussions implies that our estimates of the economic burden of the considered NCDs are likely to be conservative. Another issue with the production function-based framework is that we consider the impact of health on growth, but do not model a channel linking growth to health.[8] Incorporating such a channel would be challenging in the absence of good evidence on the causal pathways of interest and would introduce additional complexity into the model. Nevertheless, abstracting from a feedback effect of economic growth on health clearly implies that the economic burden of NCDs that we calculate is likely to be a lower bound for the true costs.

3. The model

We aim to quantify the economic burden of a particular disease, which requires us to compare economic performance between two scenarios: a status quo scenario, in which GDP is projected to grow based on current estimates and projections of disease prevalence, and a counterfactual scenario, in which the disease is eliminated from the beginning of the time period of interest. We define the overall economic impact of the relevant disease as the cumulative difference between status quo GDP and counterfactual GDP in each year (summed over the time period of interest). This framework is very flexible and allows us to examine alternative scenarios in which GDP is calculated for a designated percentage reduction in the prevalence of a specific disease.

3.1. Human capital, physical capital, and aggregate output

Consider an economy populated by individuals of different age a in which time $t \in [0, \infty)$ evolves discretely. Individuals of age group a are endowed with $h_t^{(a)}$ units of human capital and supply $\ell_t^{(a)}$ units of labour from age 15 up to their retirement at age R, i.e., for $a \in [15, R]$. Children below the age of 15 and retirees above the age of R do not work. At the aggregate level are two production factors: physical capital (K_t) and human capital (H_t). Human capital is defined as the aggregate age-specific effective labour supply

$$H_t = \sum_{a=15}^{R} h_t^{(a)} \ell_t^{(a)} N_t^{(a)}, \tag{1}$$

where $N_t^{(a)}$ denotes the number of individuals belonging to age group a. Note that aggregate human capital is greater if more individuals of working age live in the economy (i.e., $N_t = \sum_{a=15}^{R} N_t^{(a)}$ is larger), if those individuals are endowed with more human capital because they are either better educated or have more experience (i.e., $h_t^{(a)}$ is higher for at least one a), and if individuals in the economy supply more labour (i.e., $\ell_t^{(a)}$ is higher for at least one a).

Aggregate output Y_t is used for three purposes: to pay treatment costs $TC_{j,t}$[9] for disease $j \in \mathscr{J}$, where $\mathscr{J}$ is the set of diseases; to consume the quantity C_t; and to save. As a consequence, physical capital (K) accumulates according to

$$K_{t+1} = (1-\delta)K_t + Y_t - C_t - \sum_{j \in \mathscr{J}} TC_{j,t} = (1-\delta)K_t + s_t Y_t, \tag{2}$$

where δ is the rate of depreciation and s_t refers to the saving rate. From Eq. (2) it follows that the saving rate is defined as

$$s_t = 1 - \frac{C_t + \sum_{j \in \mathscr{J}} TC_{j,t}}{Y_t}.$$

Building upon Lucas (1988), aggregate output is given by the production function

$$Y_t = A_t K_t^{\alpha} \left(\sum_{a=15}^{R} h_t^{(a)} \ell_t^{(a)} N_t^{(a)} \right)^{1-\alpha}, \tag{3}$$

where A_t is the technological level of the economy that evolves exogenously and α is the elasticity of final output with respect to physical capital. The aggregate production function takes into account that output is not only produced with physical capital and *raw labour* as in the Solow (1956) framework on which the original EPIC model relies, but with *effective labour*, of which human capital is a central determinant. For simplicity, we assume that the human capital levels of different cohorts are perfect substitutes. With this assumption, the costs of NCDs are estimated in a conservative way. The reason is that, under this assumption, older workers who are disproportionately affected by NCDs can be replaced by younger workers without any frictions. Assuming imperfect substitutability of different age groups would drive up the economic impact of NCDs and thereby strengthen our central conclusions.[10]

We follow Mincer (1974) and construct average human capital of the cohort aged a according to an exponential function of education and work experience:

$$h_t^{(a)} = \exp[\eta_1 (ys_t^{(a)}) + \eta_2 (a - ys_t^{(a)} - 5) + \eta_3 (a - ys_t^{(a)} - 5)^2], \tag{4}$$

where η_1 is the semi-elasticity of human capital with respect to average years of education as given by $ys_t^{(a)}$, and η_2 and η_3 are the semi-elasticities of human capital with respect to the experience of the workforce () and the experience of the workforce squared $(a - ys_t^{(a)} - 5)^2$, respectively. The specification for experience is based on the assumption that the age of five is the earliest age at which children enter school. The values for the parameter η_1 are country-specific and taken from the studies surveyed by Psacharopoulos and Patrinos (2018), while the values for η_2 and η_3 are taken from Heckman et al. (2006).

Non-communicable diseases exert influence on the economy via three pathways: i) via effective labour supply in two ways: first, disease-

[8] The nature of the relationship between health and growth and the potential for reverse causality have been debated extensively in both the macroeconomics and microeconomics literature (see, for example, Acemoglu and Johnson, 2007; Acemoglu and Johnson, 2014; Aghion et al., 2011; Bloom et al., 2004; Bloom, Canning and Fink, 2014; Cervellati and Sunde, 2011; Cutler et al., 2006; Pritchett and Summers, 1996; Weil, 2007; Weil, 2014). While health and income are typically highly correlated, the precise nature of the relationship remains controversial because of the difficulties associated with identifying the causal effects of interest.

[9] These costs refer to the costs of ongoing treatment and are best characterized by the direct costs of healthcare including hospitalization, medication, etc.

[10] For the implications of an imperfect substitutability between different production factors see, for example, Griliches (1969), Krusell et al. (2000) and Acemoglu (2002). For a recent contribution that analyzes the extent to which different workers can be substituted, see Jäger (2016).

induced mortality reduces the population and hence the number of workers, and second, the associated morbidity reduces individual productivity and increases absenteeism; ii) via the average human capital level because NCDs disproportionately affect older age groups who may have fewer years of schooling but have accumulated more experience;[11] and iii) via physical capital accumulation in the sense that savings finance part of the treatment costs, reducing physical capital accumulation.

3.2. Impact on labour supply

The evolution of labour supply in the status quo scenario is given by

$$L_t^{(a)} = N_t^{(a)} \ell_t^{(a)} \qquad \text{with} \qquad N_t^{(a)} = [1 - \sigma_{t-1}^{(a-1)}] N_{t-1}^{(a-1)}, \tag{5}$$

where $\sigma_t^{(a)}$ is the overall mortality rate of age group a.

In the counterfactual scenario, we assume that a certain disease $i \in \mathscr{I}$ is eliminated. In order to express the impact of this on mortality, it is helpful to draw on the relationship

$$(1 - \sigma_t^{(a)}) = (1 - \sigma_{i,t}^{(a)})(1 - \sigma_{-i,t}^{(a)}), \tag{6}$$

where $\sigma_{i,t}^{(a)}$ and $\sigma_{-i,t}^{(a)}$ denote the mortality rates of people in age group a due to the eliminated disease i and due to all other causes (except i), respectively.

In general, an NCD i reduces labour supply by reducing the population $N_t^{(a)}$ (through $\sigma_{i,t}^{(a)}$). In the counterfactual case, where the disease is eliminated from time $t = 0$ onward, the evolution of labour supply is defined similarly to Eq. (5), but with a different overall mortality rate ($\sigma_{-i,t}^{(a)}$ instead of $\sigma_t^{(a)}$). For simplicity, we assume that the number of births is the same in both cases at each point in time t. In general, this is a good approximation because most NCDs affect older adults who contribute little to overall fertility.

In the counterfactual scenario, the size of the cohort aged a at time t ($\bar{N}_t^{(a)}$) evolves according to

$$\bar{N}_t^{(a)} = [1 - \sigma_{-i,t-1}^{(a-1)}] \bar{N}_{t-1}^{(a-1)}, \quad \bar{N}_0^{(a)} = N_0^{(a)}, \quad \bar{N}_t^{(0)} = N_t^{(0)}.$$

More specifically, if $a > t$, then this cohort was born before the elimination of disease i such that

$$\begin{aligned} \bar{N}_t^{(a)} &= [1 - \sigma_{-i,t-1}^{(a-1)}][1 - \sigma_{-i,t-2}^{(a-2)}] \bar{N}_{t-2}^{(a-2)} \ldots \\ &= \prod_{\tau=0}^{t-1} [1 - \sigma_{-i,t-1-\tau}^{(a-1-\tau)}] \bar{N}_0^{(a-t)} = \prod_{\tau=0}^{t-1} [1 - \sigma_{-i,t-1-\tau}^{(a-1-\tau)}] N_0^{(a-t)}, \end{aligned} \tag{7}$$

where $N_0^{(a-t)}$ is the size of the respective cohort when it was aged $a - t$ at the point of the elimination of the disease. If, by contrast, $a \leqslant t$, then this cohort was born after the elimination of disease i such that

$$\begin{aligned} \bar{N}_t^{(a)} &= [1 - \sigma_{-i,t-1}^{(a-1)}][1 - \sigma_{-i,t-2}^{(a-2)}] \bar{N}_{t-2}^{(a-2)} \ldots \\ &= \prod_{\tau=0}^{a-1} [1 - \sigma_{-i,t-1-\tau}^{(a-1-\tau)}] \bar{N}_{t-a}^{(0)} = \prod_{\tau=0}^{a-1} [1 - \sigma_{-i,t-1-\tau}^{(a-1-\tau)}] N_{t-a}^{(0)}, \end{aligned} \tag{8}$$

where $N_{t-a}^{(0)}$ is the size of the birth cohort in year $t - a > 0$ after the elimination of the disease. The two expressions differ i) by the upper bound of the product, which measures cumulative post-elimination mortality down to the year of elimination for $a > t$ and down to the birth year of the cohort for $a \leqslant t$; and ii) by the cohort size in the year in which the cohort enters the calculation, this year being the year of elimination $t = 0$ for $a > t$ and the birth year $t - a$ for $a \leqslant t$.

For the status quo scenario, the two expressions

$$N_t^{(a)} = \prod_{\tau=0}^{(t-1)} [1 - \sigma_{t-1-\tau}^{(a-1-\tau)}] N_0^{(a-t)} \qquad \text{and}$$

$$N_t^{(a)} = \prod_{\tau=0}^{(a-1)} [1 - \sigma_{t-1-\tau}^{(a-1-\tau)}] N_{t-a}^{(0)}$$

describe the size of the cohort depending on whether it was born before or after the eradication of disease i. Combining these with the RHS expressions of Eqs. (7) and (8), respectively, and drawing on the relationship in (6) we obtain the population sizes

$$\bar{N}_t^{(a)} = N_t^{(a)} \Big/ \prod_{\tau=0}^{(t-1)} [1 - \sigma_{i,t-1-\tau}^{(a-1-\tau)}] \qquad \text{and}$$

$$\bar{N}_t^{(a)} = N_t^{(a)} \Big/ \prod_{\tau=0}^{(a-1)} [1 - \sigma_{i,t-1-\tau}^{(a-1-\tau)}]$$

for the two counterfactual cases. In sum, we therefore arrive at

$$\bar{N}_t^{(a)} = N_t^{(a)} \Big/ \prod_{\tau=0}^{\min\{t,a\}-1} [1 - \sigma_{i,t-1-\tau}^{(a-1-\tau)}], \tag{9}$$

which accounts for the fact that the mortality-driven loss of labour accumulates over the years.

The morbidity effect of the disease does not change the population size, but affects the labour participation rate because people with an illness typically reduce their labour supply (either by reducing working hours or by leaving the workforce). Unlike the mortality effect, tracing the accumulation of morbidity effects over time is complicated because people affected by morbidity can be cured and, hence, increase their labour supply again in later time periods. To capture this fact, we assume that, in each year, an ill person has a probability $(1 - p_i)$ of recovering from the disease. We assume that this probability stays constant over time and that it is independent of the number of years the person lived with the disease. The value of p_i can then be easily inferred from the average duration of the disease through

$$p_i = 1 - \frac{1}{\text{duration of the disease}}.$$

Because the impact of morbidity is hard to estimate directly, we first define

$$\xi_i^{(a)} = \frac{\text{loss of labour due to morbidity in age group } a}{\text{loss of labour due to mortality in age group } a}. \tag{10}$$

Next, we assume that the following holds in any given year for age group a:

$$\xi_i^{(a)} = \frac{YLD_i^{(a)}}{YLL_i^{(a)}}, \tag{11}$$

where $YLD_i^{(a)}$ represents the years lived with disease i and $YLL_i^{(a)}$ represents the years of life lost due to disease i. Notice that $\xi_i^{(a)}$ can be calculated from the corresponding DALY data reported by the Institute for Health Metrics and Evaluation (2013).

Now consider a cohort aged a at time t, and let $m_i^{(a)}$ be the rate of people leaving the labour force due to morbidity of disease i. Then, if (11) is fulfilled, it is easy to see that

$$m_i^{(a)} = \xi_i^{(a)} \sigma_{i,t}^{(a)}.$$

Unlike labour supply, which can be derived recursively according to Eq. (5), the evolution of the labour participation rate is more complicated. People of different ages have different labour participation rates, so a recursive framework cannot be adopted. For tractability, we assume that the labour participation rate for people who are not affected by disease i is exogenously given. Specifically, we define $\hat{\ell}_t^{(a)}$ to be the labour participation rate of people without the disease. Because the morbidity effect drives workers out of the labour force, the status quo labour participation rate is expected to be smaller than $\hat{\ell}_t^{(a)}$. Notice that the difference comes from two sources: newly affected people who leave the labour force and people who left the labour force due to disease i years ago and have not yet recovered. To fix the distortion

[11] Note that another pathway exists by which a poor health condition affects human capital that we do not account for by our specification: absenteeism due to poor health might lead to faster depreciation of human capital because it sits idle.

caused by discretisation, we assume that i) at the beginning of year t, the labour force $\ell_t^{(a)}$ is calculated, and ii) at the end of each year, morbidity effects are factored into the population.

Now we restrict our attention to the cohort aged a at time t. Notice that $\ell_t^{(a)}$ is determined by i) the labour participation rate of "healthy" people ($\hat{\ell}_t^{(a)}$) and ii) the fraction of "healthy" people at the beginning of year t ($F^{(a)}$). Here, "healthy" means that the person has not left the workforce due to morbidity, while the labour participation rate of the "unhealthy" simply equals zero.

Proposition 1. For the cohort aged a at time t, the fraction of "healthy" people at the beginning of year t can be approximated by

$$F^{(a)} \approx \prod_{\tau=0}^{a-1} [1 - p_i^{\tau} m_i^{(a-1-\tau)}].$$

Proof. The case for $a = 1$ is trivial. We therefore prove the proposition by induction. Suppose that

$$F^{(n)} \approx \prod_{\tau=0}^{n-1} [1 - p_i^{\tau} m_i^{(n-1-\tau)}].$$

Then consider age $n + 1$, where, with probability p_i, those who are sick at the beginning of age n, $(1 - F^{(n)})$ will still be sick, whereas the others return to the labour force. Then, the disease will again claim a fraction $m_i^{(n)}$ of the total "healthy" population each year. Given that $m_i^{(n)}$ for $n = 1, 2, \ldots$ is small, we have

$$\begin{aligned} F^{(n+1)} &= [1 - p_i(1 - F^{(n)})](1 - m_i^{(n)}) \\ &\approx \left(1 - p_i\{1 - \prod_{\tau=0}^{n-1} [1 - p_i^{\tau} m_i^{(n-1-\tau)}]\}\right)(1 - m_i^{(n)}) \\ &\approx \prod_{\tau=0}^{n} (1 - p_i^{\tau} m_i^{(n-\tau)}). \end{aligned} \tag{12}$$

Note that, in this case, we assume that morbidity only affects the participation rate and that it is completely independent of the mortality process. We can now write the approximate relationship between $\ell_t^{(a)}$ and $\hat{\ell}_t^{(a)}$ as

$$\ell_t^{(a)} \approx \hat{\ell}_t^{(a)} F^{(a)} = \hat{\ell}_t^{(a)} \prod_{\tau=0}^{a-1} [1 - p_i^{\tau} m_i^{(a-1-\tau)}]. \tag{13}$$

Although the closed-form solution can be obtained by induction, we prefer to use this approximation for two reasons: first, the complexity is greatly reduced without sacrificing much in the way of accuracy, and second, this approximation provides a very intuitive interpretation and is directly comparable to Eq. (9).

The next step is to generate the labour participation rate of the counterfactual case ($\bar{\ell}_t^{(a)}$) from that of the status quo case ($\ell_t^{(a)}$). Notice that here $\bar{\ell}_t^{(a)}$ is different from $\hat{\ell}_t^{(a)}$. The former represents the labour participation rate of the counterfactual case in which the disease is eliminated from $t = 0$ onward; the latter is the labour participation rate of "healthy" people. If $a \leqslant t$, the cohort was born after the elimination of disease i and hence we have $\bar{\ell}_t^{(a)} = \hat{\ell}_t^{(a)}$ (everyone is "healthy" in this cohort). If $a > t$, then the cohort was born before the elimination of the disease. In this case, some members of the cohort may have contracted the disease before $t = 0$ and may not have recovered yet. Knowing this, we have the following:

$$\bar{\ell}_t^{(a)} = \hat{\ell}_t^{(a)}, \qquad t \geqslant a, \tag{14}$$

$$\bar{\ell}_t^{(a)} \approx \hat{\ell}_t^{(a)} \prod_{\tau=t}^{a-1} [1 - p_i^{\tau} m_i^{(a-1-\tau)}], \qquad t < a. \tag{15}$$

Combining (13), (14), and (15), we get

$$\begin{aligned} \bar{\ell}_t^{(a)} &\approx \ell_t^{(a)} \Big/ \prod_{\tau=0}^{\min\{t,a\}-1} [1 - p_i^{\tau} m_i^{(a-1-\tau)}] \\ &= \ell_t^{(a)} \Big/ \prod_{\tau=0}^{\min\{t,a\}-1} [1 - p_i^{\tau} \sigma_{i,t-1-\tau}^{(a-1-\tau)} \xi_i^{(a-1-\tau)}]. \end{aligned} \tag{16}$$

From Eq. (13), we see that a larger p_i leads to a lower participation rate, i.e., the morbidity effect is more likely to accumulate over the years if the disease is hard to cure. The intuition behind Eq. (16) is the following: the different exposure to the disease drives the difference between the labour participation rate of the status quo ($\ell_t^{(a)}$) and the counterfactual case ($\bar{\ell}_t^{(a)}$). For $a \leqslant t$, the cohort in the counterfactual case avoided exposure to the disease completely in the previous a years. For $a > t$, the cohort only avoided exposure to the disease in the most recent t years.

Overall, the loss of labour supply in age group a at time t can be calculated as

$$\Delta L_t^{(a)} = \bar{L}_t^{(a)} - L_t^{(a)} = L_t^{(a)} M_{i,t}^{(a)}, \tag{17}$$

with $L_t^{(a)} = \ell_t^{(a)} N_t^{(a)}$ as status quo labour supply and

$$\begin{aligned} M_{i,t}^{(a)} &:= \frac{1}{\prod_{\tau=0}^{\min\{t,a\}-1} [1 - p_i^{\tau} m_i^{(a-1-\tau)}][1 - \sigma_{i,t-1-\tau}^{(a-1-\tau)}]} - 1 \\ &\approx \sum_{\tau=0}^{\min\{t,a\}-1} \sigma_{i,t-1-\tau}^{(a-1-\tau)} [1 + p_i^{\tau} \xi_i^{(a-1-\tau)}]. \end{aligned} \tag{18}$$

The approximation in Eq. (18) results from the observation that $\sigma_{i,t}^{(a)}$ and $\xi_i^{(a)}$ are typically small numbers. Intuitively, $M_{i,t}^{(a)}$ can be interpreted as the cumulative labour supply impact of disease i on the cohort aged a at time t. By substituting (17) into (1), the loss of human capital due to disease i at time t can be written in percentage terms as

$$\frac{\Delta H_t}{H_t} = \frac{\sum_{a=15}^{R} h_t^{(a)} \ell_t^{(a)} N_t^{(a)} M_{i,t}^{(a)}}{\sum_{a=15}^{R} h_t^{(a)} \ell_t^{(a)} N_t^{(a)}}. \tag{19}$$

Eq. (19) implies that the human capital loss is related to the country's demographic structure. Even if the mortality and morbidity effects of a disease were similar in two countries for each age group (similar $M_{i,t}^{(a)}$ for both countries), the aggregate human capital loss could still vary substantially due to the different weights ($h_t^{(a)} \ell_t^{(a)} N_t^{(a)}$) on each age group.

Now, instead of completely eliminating the disease, suppose that the intervention only reduces the disease prevalence by a certain percentage, say ρ. The previous discussion still holds true, and we can obtain the loss of labour by replacing ($\sigma_{i,t}$, $m_{i,t}$) with ($\rho\sigma_{i,t}$, $\rho m_{i,t}$) in (18). Denoting the loss of labour for age group a at time t in case of a reduction in the disease prevalence by ρ as $\Delta L_t^{(a)}(\rho)$, it is easy to show that

$$\begin{aligned} \Delta L_t^{(a)}(\rho) &\approx \ell_t^{(a)} N_t^{(a)} \sum_{\tau=0}^{\min\{t,a\}-1} \rho \sigma_{i,t-1-\tau}^{(a-1-\tau)} [1 + p_i^{\tau} \xi_i^{(a-1-\tau)}] \\ &\approx \rho L_t^{(a)} M_{i,t}^{(a)}, \end{aligned} \tag{20}$$

where $M_{i,t}^{(a)}$ is defined in (18) and the approximation is valid when $\sigma_{i,t}$ and $m_{i,t}$ are small. Eq. (20) shows that the cumulative loss of labour is approximately linear with respect to disease prevalence averted (ρ), given that the mortality and morbidity of the disease are small.[12]

[12] Note that we abstract from repercussions of mortality and morbidity on migration and fertility. In the countries that we consider, this assumption is rather innocuous because i) morbidity and mortality are already so low that they are negligible in migration decisions and ii) NCDs predominantly affect older cohorts, which limits the impact on fertility decisions. However, in less developed countries, high rates of mortality and morbidity among younger age groups might lead to outward migration and to higher fertility. This could be

Our approach is based on the assumption of independence between the mortality and morbidity rates of different diseases. This is convenient from a technical perspective and allows us to circumvent the necessity of imposing arbitrary assumptions on the structure of co-morbidities. Regarding the benefits of a 100% elimination of the NCDs we consider, our assumption of independence between the mortality and morbidity rates of different diseases is less of a concern. While there could still be spillover effects on other NCDs that we do not capture, assuming that morality or morbidity in the eliminated disease is not replaced by mortality or morbidity in another, these spillover effects would likely reduce mortality and morbidity in other domains such that our cost estimates are conservative. In the case of a partial disease elimination, there are three possible effects: i) reducing the prevalence of one disease (e.g., diabetes) can be expected to reduce the prevalence of secondary disorders (e.g., cardiovascular disease). This effect in isolation would imply that a particular health intervention becomes even more worthwhile because of the spillovers of this intervention on the prevalence of sequelae. This epidemiological channel is complemented by two behavioural channels: ii) as Murphy and Topel (2006) show, complementarities in the value of life-saving imply that reductions in the mortality from one disease (e.g., heart disease) raise the willingness to pay for lowering mortality from another disease (e.g., cancer). Running counter to this, iii) the elimination of health risks may induce individuals to engage in less healthy lifestyles. For example, if a treatment becomes available that reduces the risk of dying because of cancer, fewer people might quit smoking. The offsetting nature of these channels reduces their empirical relevance. However, the consideration of interdependencies between diseases and the behavioural responses of individuals open interesting avenues for further research.

3.3. Impact on physical capital accumulation

Given disease $i \in \mathscr{I}$ is eliminated in the counterfactual, we need to set the treatment cost $TC_{i,t}$ related to disease i to zero in Eq. (2). The accumulation of physical capital can then be written as

$$\bar{K}_{t+1} = \bar{Y}_t - \bar{C}_t + (1-\delta)\bar{K}_t - \sum_{j \in \mathscr{I}, j \neq i} TC_{j,t}, \tag{21}$$

where an "overbar" indicates that the corresponding variable refers to the counterfactual scenario.[13] Because the disease is assumed to be eliminated, the resources that were devoted to its treatment can now be used for saving or for consumption. Notice that this creates an income effect which, in reality, could affect the division of households' income between saving and consumption. For tractability, we assume that, in the counterfactual scenario, aggregate investment consists of two parts: a fixed share s_t of total output and an additional part $\chi TC_{i,t}$, with $\chi \in [0, 1]$, representing the portion that would otherwise have been used to pay for the treatment of disease i:

$$\bar{I}_t = \bar{Y}_t - \bar{C}_t - \sum_{j \in \mathscr{I}, j \neq i} TC_{j,t} = s_t \bar{Y}_t + \chi TC_{i,t}.$$

In this expression, χ is the fraction of the recovered treatment cost that is channelled into savings, and we obtain the counterfactual saving rate

$$\bar{s}_t = \frac{s_t \bar{Y}_t + \chi TC_{i,t}}{\bar{Y}_t}. \tag{22}$$

As a result, the saving rate increases whenever at least some of the recovered treatment cost is converted into savings.

For our scenario with partial elimination at rate ρ, we consider $\bar{I}_t = s_t \bar{Y}_t + \rho\chi TC_{i,t}$ and, thus,

$$\bar{s}_t = \frac{s_t \bar{Y}_t + \rho\chi TC_{i,t}}{\bar{Y}_t}. \tag{23}$$

For the partial elimination of a disease we thus assume that the treatment cost is added back to savings in proportion. We realize that the situation may again be more complicated in the presence of multimorbidity, where treatment costs have been shown to be interdependent for the US (see Dielemann et al., 2016). In the absence of good data for the East Asian countries under consideration, we maintain our assumption of independence. Since the treatment costs are higher if a patient suffers from more than one disease, we would conjecture that our estimates are on the conservative side.

In summary, our approach has the following advantages over the standard EPIC tool: first, we account for morbidity by adjusting the labour participation rate for each disease based on data from the Institute for Health Metrics and Evaluation (2013); second, we infer the impact of a disease on physical capital accumulation by obtaining χ and $TC_{i,t}$ directly from the data; and third, we model human capital accumulation by employing a Mincerian specification that allows for consideration of years of education and experience.

4. Results

We present direct estimates for five major conditions— ischemic heart disease, cerebrovascular disease, diabetes, chronic obstructive pulmonary disease (COPD), and breast cancer. The results are then scaled up using Institute for Health Metrics and Evaluation (2013) data on DALYs to reflect the four NCDs that are the focus of the United Nations (cardiovascular diseases, cancer, chronic respiratory diseases, and diabetes), plus mental health conditions. Altogether, these diseases account for 67% of all DALYs related to NCDs in China, 54% in Japan, and 58% in South Korea. The scaling is implemented by calculating the proportion of DALYs in a particular domain (e.g., cancer) that the relevant disease accounts for in EPIC (breast cancer in this instance). If breast cancer accounts for 10% of the total DALYs lost to cancer, the scaling factor applied to our results for breast cancer to obtain a result for all cancers is 10. Scaling factors are calculated for each country. Similarly, we use WHO data on mental illness DALYs to include estimates of economic losses from mental health conditions. The mental health scaling factor is calculated by obtaining the ratio of DALYs accounted for by the four NCD domains to the DALYs accounted for by mental health conditions. Obtaining comprehensive information on the treatment costs associated with each disease is difficult. As Table A1 shows, we calculated treatment costs from various sources. For the missing data, we adjusted for cross-country differences using data on health expenditures per capita from the World Bank database, adjusted to account for inflation. In addition, for each country we assumed a fixed annual growth rate of the per capita treatment costs to adjust for

Table 1
Parameter values and data sources.

Parameter	Value	Source
α	0.4–0.48	e.g., Jones (1995) and Feenstra et al. (2015)
δ	0.05	e.g., Grossmann et al. (2013)
s	country specific	World Bank (2015)
η_1	0.073–0.102	Psacharopoulos and Patrinos (2018), Hall and Jones (1999)
η_2	0.1301	Heckman et al. (2006)
η_3	−0.0023	Heckman et al. (2006)
ξ_i	country specific	Institute for Health Metrics and Evaluation (2013)
χ_i	country specific	World Bank (2015)

(*footnote continued*)
relevant when analyzing the effects of communicable diseases that are more common in less developed countries and have a higher prevalence among younger age groups (see also Luca et al., 2018 in the context of the human papillomavirus).

[13] It is straightforward to include intervention costs in the accumulation equation for physical capital if the model were applied in a cost-benefit analysis (see Bloom et al. (2017) which is the working paper version of this article).

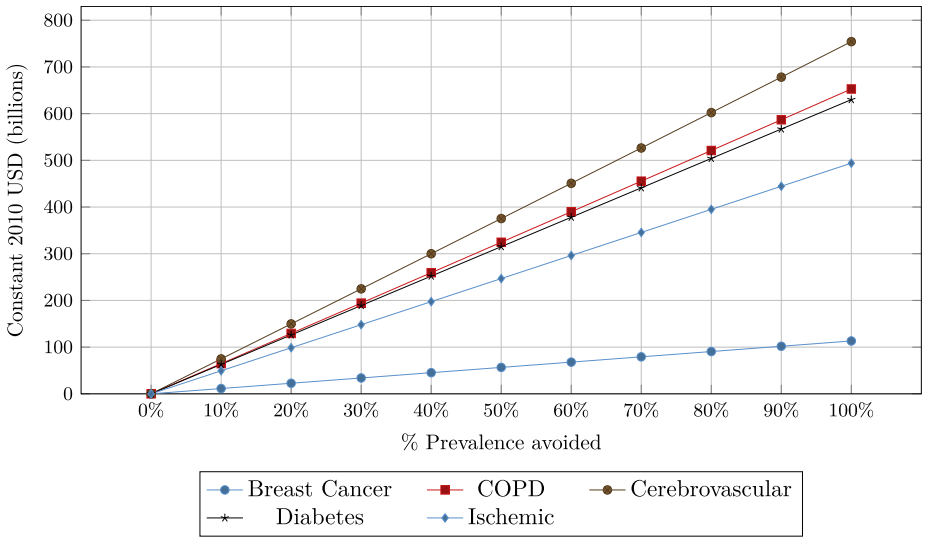

Fig. 2. GDP benefit associated with averted disease prevalence for China (in billions of 2010 USD).

rising medical costs. The annual growth rate for per capita health expenditure from 2005 to 2014 approximates this number, which is 13.4% for China, 4.6% for Japan, and 7.8% for South Korea. The treatment cost estimates in 2010 are listed in Table A2 in the Appendix. The GDP projections for the status quo scenario are taken from the World Bank (2017). We rely on the International Labour Organization (2015) for age-specific labour force projections, the Barro and Lee (2013) education database for age-specific data on average years of schooling, and Feenstra et al. (2015) for the country-specific elasticities of output with respect to physical capital. Table 1 describes other data sources.

We show disease-specific estimates (ischemic heart disease, cerebrovascular disease, diabetes, chronic obstructive pulmonary disease, and breast cancer, before scaling) for each % of disease prevalence averted for China (Fig. 2), Japan (Fig. 3) and South Korea (Fig. 4). Table 2 shows the disease-specific burden for the three countries, while Table 3 contains the scaled estimates and the total disease burden for the five domains we are interested in (100% of mortality averted for cardiovascular diseases, cancer, chronic respiratory diseases, diabetes, and mental health conditions) for the period 2010–2030.

Figs. 2–4 display, by disease, the estimated cost savings for a given percentage of prevalence averted. To derive this number, we calculate the output trajectory of the country under consideration for the time period 2010 to 2030 under both the status quo scenario without intervention and the counterfactual scenario for a given reduction in disease prevalence. The cumulative difference between the two scenarios is then the cost saving due to the intervention that reduces the particular disease in the particular country by the given amount. For example, the estimate at 10% compares the cumulative difference in GDP between the status quo scenario with disease prevalence as predicted and the counterfactual scenario in which disease prevalence is reduced by 10%. We repeat this for the whole range of counterfactual scenarios from a 1% reduction to a 100% reduction and plot the resulting numbers in the figures. The results are shown in billions of real USD with a base year of 2010.[14]

Our estimates indicate that the most costly condition varies by country, although breast cancer is generally the least costly. For example, in China the most costly condition is cerebrovascular disease, and in Japan and South Korea it is diabetes. Interestingly, COPD is expected to cost China 653 billion USD over the two decades. This is roughly 8.4% of China's total loss, compared with only 2.1% in Japan and 4% in South Korea. The high prevalence of COPD in China is related to its air pollution and the large fraction of its population that smokes. Overall, the ranking of the impact of the other non-communicable diseases varies among the three countries. Finally, we observe that the cost estimates increase roughly linearly with disease prevalence averted. This linearity is not surprising because Eq. (20) is a good approximation of the loss in labour supply given that the mortality related to each disease is small.

The final row of Table 3 shows the estimates of the total impact of non-communicable diseases in the five domains (cardiovascular diseases, cancer, chronic respiratory diseases, diabetes, and mental health conditions) after the estimates for the individual diseases have been scaled. Estimates are again given in real USD with a base year of 2010 for the period 2010–2030. The results indicate that the total economic costs for these five NCD domains are 7.7 trillion USD in China, 3.5 trillion USD in Japan, and 1 trillion USD in South Korea.

As previous estimates using the production function-based approach have not included the treatment cost mechanism, we investigate the contribution of this pathway to our estimates of the overall burden. Table A3 in the Appendix shows model estimates in which we exclude treatment costs, and we use these results to establish the contribution of treatment costs to the overall total in Fig. 5. For China, treatment costs account for 56% of the costs of the NCDs that we consider, while the corresponding figure is 22% for Japan and 38% for South Korea. The relatively higher contribution of treatment costs in China can partly be explained by its large gross saving rate (around 50% according to the World Bank), compared with that of Japan (22%) and South Korea (35%).[15] In our model, χ in Eq. (22) is approximated by the saving rate. A higher saving rate means that a larger proportion of resources used in treatment could otherwise be used as investment in physical capital. This leads to a larger output loss for countries with a higher saving rate. A second lever to the high treatment cost effect in China lies with the high rate of treatment cost inflation (13.4%, as compared to 4.6% for Japan and 7.8% for South Korea). Other differences in the relative

[14] Note that we do not discount these numbers and instead present them as cumulative real output losses. This circumvents the problem of attaching a social discount rate, the value of which is not uncontroversial (see, for example, Ramsey (1928); Caplin and Leahy (2004)).

[15] The high saving rate in China often raises concerns that the economy is already dynamically inefficient. Whether or not this is the case does not change our results, however. See Bloom et al. (2014) for a thorough discussion.

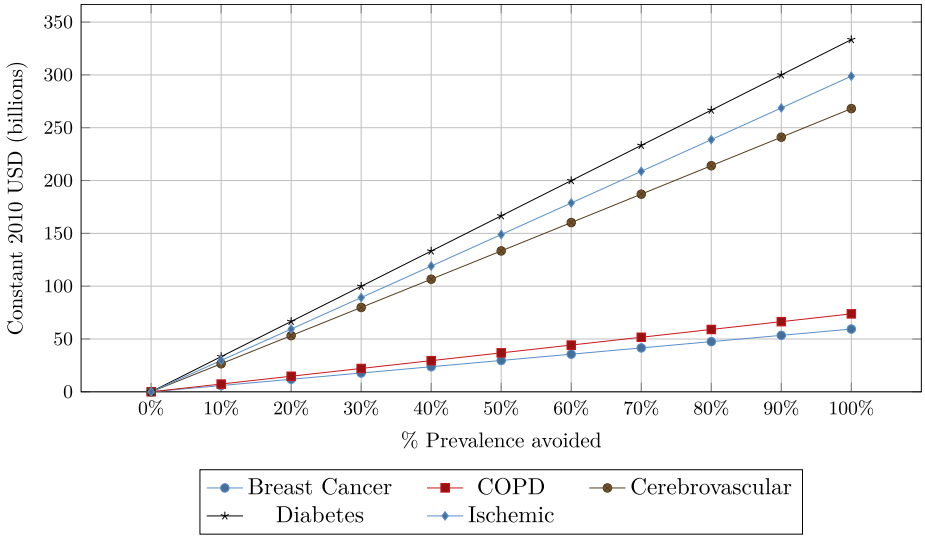

Fig. 3. GDP benefit associated with averted disease prevalence for Japan (in billions of 2010 USD).

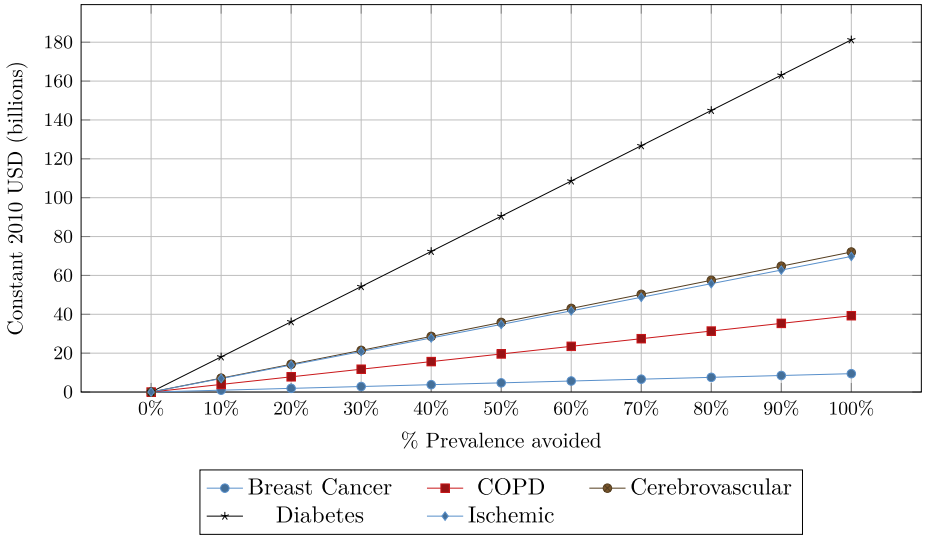

Fig. 4. GDP benefit associated with averted disease prevalence for South Korea (in billions of 2010 USD).

Table 2
Estimates of disease burdens (100% of prevalence averted) for ischemic heart disease, cerebrovascular disease, diabetes, COPD, and breast cancer over the period 2010–2030 in 2010 USD (billions).

Disease	China	Japan	South Korea
Ischemic Heart Disease	494	299	70
Cerebrovascular Disease	754	268	72
Diabetes	630	333	181
COPD	653	74	39
Breast Cancer	113	59	9

Note: The numbers are calculated under the assumption that intervention costs to (partially) eliminate the diseases are zero.

Table 3
Scaled estimates of NCD disease burdens (100% of prevalence averted) for cardiovascular diseases, diabetes, chronic respiratory diseases, cancer, and mental health conditions over the period 2010–2030 in 2010 USD (billions).

Disease	China	Japan	South Korea
Cardiovascular Diseases	1,504	756	173
Diabetes	630	333	181
Chronic Respiratory Diseases	777	129	64
Cancer	3,328	1,485	286
Mental Health Conditions	1,497	838	268
Total of the Five Domains	**7,737**	**3,542**	**973**

Note: The numbers are calculated under the assumption that intervention costs to (partially) eliminate the diseases are zero.

contribution of this pathway are likely due to heterogeneity in the prevalence of different conditions and the design of the health care system. Overall, our calculations highlight the importance of incorporating the treatment cost mechanism into the model as an additional pathway for estimating the economic impact of chronic conditions.

The upper panel of Table 4 provides the estimate of the total burden for the five NCD domains using different measures of economic performance. The total burden of these NCDs (100% reduction), if measured as a percentage of aggregate GDP in 2010, is largest in China with

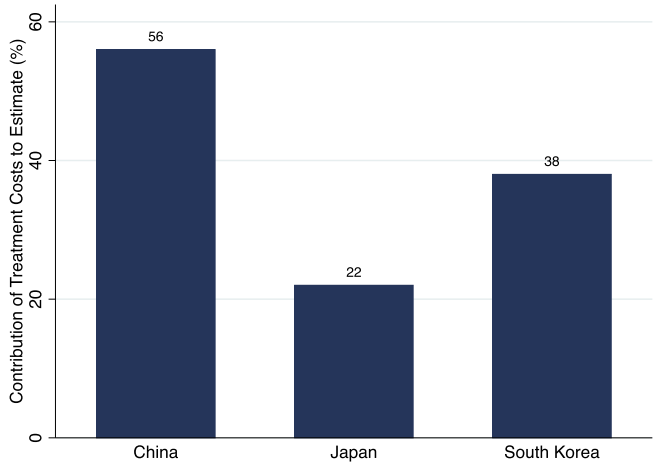

Fig. 5. Percent contribution of treatment costs to total estimate.

127%, followed by South Korea with 89%, and Japan with 62%. This measure, albeit straightforward, is biased in that it leads to a larger proportional burden for countries with higher growth potential. Thus, the result is partly explained by the fact that China is expected to enjoy a much higher GDP growth rate than Japan or South Korea. The per capita figures[16] show that Japan has the highest NCD burden with a per capita loss of $28,362 (constant USD with the base year 2010), compared with only $5,438 in China and $19,216 in South Korea. Because Japan has the highest per capita GDP and health expenditure, the cost of each unit of mortality and morbidity is higher for the Japanese. The third measure in Table 4 shows that the burden of the three countries is actually relatively similar if adjusted for the income level (or GDP per capita) and for the growth potential. The burden is equivalent to an annual tax of 3.42% on the economy in China, whereas the number is 2.77% for Japan, and 3.38% for South Korea.

One question that our analysis raises is whether considering the total costs associated with NCDs as measured by reducing their prevalence to zero is reasonable. To get an estimate of the total economic burden of certain conditions, this is indeed what we would like to know. However, when assessing the impact of realistic reductions in prevalence that health policies can achieve, considering a scenario in which a particular chronic disease is eliminated is not reasonable. Chronic conditions may persist even under an ideal health care system, and even technological advances might not be sufficient to reduce their prevalence to zero. Therefore, we also consider the costs associated with NCDs in a scenario in which the corresponding case fatality rate (the proportion of reported cases of a specific disease that are fatal within a specified time frame) reaches the minimum among OECD countries. For example, we estimate the cost reduction for the case in which China has the same COPD-related case fatality rate as the OECD country with the lowest current COPD-related case fatality rate. The rationale for this analysis is that such a reduction is a realistic target because another country has already achieved it. More specifically, the lowest case fatality rates for ischemic heart disease, COPD, and cerebrovascular diseases are set to those in Slovenia, Estonia, and Slovakia, respectively. For breast cancer and diabetes, the lowest levels are set to those in Cyprus and Iceland.[17] The estimates by disease category and in total for the five NCDs under consideration are shown in Table 5. While, unsurprisingly lower than those presented in Table 2, they indicate that working toward achieving reasonable targets for reductions in the prevalence of chronic conditions are likely to have substantial payoffs in terms of reducing the costs associated with NCDs. The lower panel of Table 4 reports the estimated returns to achieving the best-practice benchmark for the five disease domains we are interested in as percentage of 2010 GDP, in per capita terms, and as percentage of total GDP over the time frame 2010–2030. The figures suggest sizeable gains.

Table 4
Burden of the five NCDs for different measures of economic performance.

	Country	% of 2010 GDP	Per Capita Loss (2010 USD)	% of Total GDP during 2010–2030
Estimates Associated with 100% Reduction of Disease Burden	China	127%	5,438	3.42%
	Japan	62%	28,362	2.77%
	South Korea	89%	19,216	3.38%
Estimates Associated with Lowest Case Fatality Rate among OECD Countries	China	50%	2,128	1.34%
	Japan	16%	7,479	0.73%
	South Korea	28%	6,109	1.07%

Note: The numbers are calculated under the assumption that intervention costs to (partially) eliminate the diseases are zero.

5. Conclusions

We implement a macroeconomic production function-based approach to assess the economic burden of non-communicable diseases. The advantage of this approach is that we can account for economic adjustment mechanisms associated with changes in disease prevalence. Using a human capital augmented production function as proposed by Lucas (1988), we incorporate morbidity and mortality effects into the model and account for the impact of treatment costs on physical capital accumulation. As we are considering age-specific human capital we can keep track of the impact of NCDs on human capital not only through a level effect but also through changes in the age-structure of the employed labour force. Our modelling of age-specific human capital allows us to take account of differences in the productivity change when the impact of NCDs varies across cohorts. We apply our approach to calculate the economic impact of non-communicable diseases for China, Japan, and South Korea, three countries experiencing rapid population ageing. Our results indicate that chronic conditions are very costly in terms of lost output, with estimates of the total burden of five major chronic diseases over the time period 2010–2013 being 7.7, 3.5 and 1 trillion (year 2010) USD. Though the losses differ significantly at both aggregate and per capita levels, the NCD burden of the three countries is rather similar after adjusting for the growth potential and the income level. In this case the figures are 3.42%, 2.77%, and 3.38% of total GDP for China, Japan, and South Korea, respectively, during 2010–2030.

Cross-country heterogeneity exists in the ranking of disease importance, which likely reflects differential exposure to risk factors, smoking patterns, and environmental pollution. A more detailed analysis of these differences is an important topic for future research. The main conclusion of the paper is that the economic burden associated with non-communicable diseases in East Asia, as elsewhere, is substantial. Efforts to tackle the spread of chronic conditions and their associated risk factors now are likely to have substantial payoffs in the future.

Fruitful avenues for further research might include (i) considering the role of co-morbidities between different diseases when assessing the benefits from partial disease elimination; (ii) exploring alternative morbidity and mortality patterns in the absence of NCDs; (iii) introducing labour supply, savings and schooling responses to the expected increase in longevity associated with the counterfactual elimination of NCDs; and (iv) relaxing the assumption of perfect substitutability between workers in different cohorts in order to assess

[16] The per capita loss is calculated based on the population size as of 2010.
[17] Estimated case fatality rates were calculated by the authors based on disease incidence and mortality rates from 2015 (GBD, 2016).

Table 5
Estimated economic burden assuming the lowest case fatality rates for the specific domain among OECD countries.

Country		Ischemic Heart Disease	Cerebrovascular Disease	Diabetes	COPD	Breast Cancer	Total Cost (See Note)
China	Mortality Reduction (%) Towards the Lowest	29%	18%	29%	59%	44%	3,027
	Burden of Excess Mortality Billions (2010 USD)	142	133	181	381	50	
Japan	Mortality Reduction (%) Towards the Lowest	52%	33%	37%	50%	14%	934
	Burden of Excess Mortality Billions (2010 USD)	153	88	124	37	8	
South Korea	Mortality Reduction (%) Towards the Lowest	36%	27%	66%	36%	10%	309
	Burden of Excess Mortality Billions (2010 USD)	25	19	119	14	1	

Note: The numbers are calculated under the assumption that intervention costs to (partially) eliminate the diseases are zero. The Total Cost is calculated for the five domains (cardiovascular diseases, cancer, chronic respiratory diseases, diabetes, and mental health conditions).

the economic effects of diseases that disproportionately affect particular age groups in a more fine-grained manner.

The model presented and applied herein is flexible and could also be used to explore the impact of other factors impinging on health such as road-traffic accidents. In addition, our approach is also relevant for modelling the impact of diseases within other domains, such as communicable diseases. In this paper we have stayed within the production function-based framework, which has the advantages of i) providing a tractable and parsimonious method for analysing the economic burden of chronic conditions, and ii) leading to a conservative estimate of the economic burden of diseases. This framework lays the ground for the development of a micro-founded computable general equilibrium model in future research.

Appendix A

Table A1
Data sources of treatment costs.

Disease	Treatment cost source
Ischemic Heart Disease	Chang et al. (2012)
Cerebrovascular Disease	Lim et al. (2009)
Diabetes	International Diabetes Federation (2015)
COPD	Nishimura and Zaher (2004)
Breast Cancer	Kim et al. (2008)

Table A2
Estimates of treatment cost per country (2010 USD).

Country	Disease	Treatment Cost per Capita (in 2010 USD)
China	Ischemic Heart Disease	$13.29
Japan	Ischemic Heart Disease	$69.39
Korea	Ischemic Heart Disease	$29.23
China	Cerebrovascular Disease	$12.97
Japan	Cerebrovascular Disease	$67.76
Korea	Cerebrovascular Disease	$28.54
China	Diabetes	$11.62
Japan	Diabetes	$242.96
Korea	Diabetes	$154.45
China	COPD	$13.32
Japan	COPD	$69.94
Korea	COPD	$26.74
China	Breast Cancer	$2.78
Japan	Breast Cancer	$15.68
Korea	Breast Cancer	$4.91

Table A3
Estimates excluding treatment costs in 2010 USD (billions).

Disease	China	Japan	Korea
Ischemic Heart Disease	182	256	51
Cerebrovascular Disease	449	227	54
Diabetes	188	159	83
COPD	340	31	22
Breast Cancer	48	50	6
Total (Including Mental Health Conditions)	3,420	2,755	606

Note: The numbers are calculated under the assumption that intervention costs to (partially) eliminate the diseases are zero.

References

Abegunde D., Stanciole A., 2006. An estimation of the economic impact of chronic noncommunicable diseases in selected countries. WHO Working Paper, Department of Chronic Diseases and Health Promotion, Geneva.

Acemoglu, D., 2002. Directed technical change. Rev. Econ. Stud. 69 (4), 781–809.

Acemoglu, D., Johnson, S., 2007. Disease and development: the effect of life expectancy on economic growth. J. Political Econ. 115 (6), 925–985.

Acemoglu, D., Johnson, S., 2014. Disease and development: a reply to Bloom, Canning, and Fink. J. Political Econ. 122 (6), 1367–1375.

Aghion, P., Howitt, P., Murtin, F., 2011. The relationship between health and growth: when Lucas meets Nelson-Phelps. Rev. Econ. Institutions 2 (1), 1–24.

Barro, R.J., 1991. Economic growth in a cross section of countries. Quart. J. Econ. 106 (2), 407–443.

Barro, R.J., Lee, J.W., 2013. A new data set of educational attainment in the world, 1950–2010. J. Dev. Econ. 104, 184–198.

Beaulieu, N., Bloom, D.E., Bloom, L.R., Stein, R., 2009. Breakaway: the global burden of cancer challenges and opportunities. In: The Economist Intelligence Unit. Livestrong, London.

Bloom, D.E., Cafiero, E., Jan-Llopis, E., Abrahams-Gessel, S., Bloom, L.R., Fathima, S., Feigl, A.B., Gaziano, T., Hamandi, A., Mowafi, M., 2012. The global economic burden of noncommunicable diseases. Program on the Global Demography of Aging, Geneva, Switzerland Technical report.

Bloom, D.E., Cafiero-Fonseca, E.T., McGovern, M.E., Prettner, K., 2014. China and India's descent into chronic disease: killing themselves slowly. Milken Institute Review, 2nd Quarter 24–33.

Bloom, D.E., Cafiero-Fonseca, E.T., McGovern, M.E., Prettner, K., Stanciole, A., Weiss, J., Bakkila, S., Rosenberg, L., 2014. The macroeconomic impact of non-communicable diseases in China and India: estimates, projections, and comparisons. J. Econ. Ageing 4, 100–111.

Bloom, D.E., Canning, D., Fink, G., 2014. Disease and development revisited. J. Political Econ. 122 (6), 1355–1366.

Bloom, D.E., Chen, S., McGovern, M.E., 2018. The economic burden of noncommunicable diseases and mental health conditions: results for Costa Rica, Jamaica, and Peru. Rev. Panam. Salud Publica 42, 18.

Bloom, D.E., Canning, D., Mansfield, R.K., Moore, M., 2007. Demographic change, social security systems, and savings. J. Monetary Econ. 54 (1), 92–114.

Bloom, D.E., Canning, D., Moore, M., 2014. Optimal retirement with increasing longevity. Scand. J. Econ. 116 (3), 838–858.

Bloom, D.E., Canning, D., Sevilla, J., 2004. The effect of health on economic growth: a production function approach. World Dev. 32 (1), 1–13.

Bloom, D.E., Chen, S., Kuhn, M., McGovern, M.E., Oxley, L., Prettner, K., 2017. The Economic Burden of Chronic Diseases: Estimates and Projections for China, Japan, and South Korea. NBER Working Paper No. 23601, Cambridge, MA.

Bloom, D.E., Chen, S., McGovern, M.E., Prettner, K., Candeias, V., Bernaert, A., Cristin, S., 2015. Economics of non-communicable diseases in Indonesia. World Economic Forum, Indonesia, Jakarta Technical report.

Bloom, D.E., Chisholm, D., Jan-Llopis, E., Prettner, K., Stein, A., Feigl, A., 2011. From burden to best buys: Reducing the economic impact of non-communicable disease in low-and middle-income countries. WHO executive summary, Geneva, Switzerland Technical report.

Bloom, D.E., Kuhn, M., Prettner, K., forthcoming. Health and economic growth. In: Oxford Encyclopedia of Economics and Finance, Oxford University Press, Oxford, UK.

Caplin, A., Leahy, J., 2004. The social discount rate. J. Political Econ. 112 (6), 1257–1268.

Chang, H.-S., Kim, H.-J., Nam, C.-M., Lim, S.-J., Jang, Y.-H., Kim, S., Kang, H.-Y., 2012. The socioeconomic burden of coronary heart disease in Korea. J. Preventive Med. Public Health 45 (5), 291–300.

Cervellati, M., Sunde, U., 2011. Life expectancy and economic growth: the role of the demographic transition. J. Econ. Growth 16 (2), 99–133.

Currie, G., Kerfoot, K.D., Donaldson, C., Macarthur, C., 2000. Are cost of injury studies useful? Injury Prevention 6 (3), 175–176.

Cutler, D., Deaton, A., Lleras-Muney, A., 2006. The determinants of mortality. J. Econ. Perspect. 20 (3), 1.

Dielemann, J.L., Baral, R., Birger, M., Bui, A.L., Bulchis, A., Chapin, A., et al., 2016. US spending on personal health care and public health, 1996–2013. J. Am. Med. Assoc. 316 (24), 2627–2646.

Durlauf, S.N., Johnson, P.A., Temple, J.R., 2005. Growth econometrics. In: Handbook of Economic Growth. vol. 1 North Holland, Amsterdam, Netherlands, pp. 555–677.

Dwyer, D.S., Mitchell, O.S., 1999. Health problems as determinants of retirement: are self-rated measures endogenous? J. Health Econ. 18 (2), 173–193.

Eberhardt, M., Teal, F., 2011. Econometrics for grumblers: a new look at the literature on cross country growth empirics. J. Econ. Surveys 25 (1), 109–155.

Frankovic, I., Kuhn, M., Wrzaczek, S., 2017. Medical progress, demand for health care, and economic performance. No. 08/2017. ECON WPS-Vienna University of Technology Working Papers in Economic Theory and Policy.

Global Burden of Disease Study 2015, 2016. Global burden of disease study 2015 (GBD 2015) results. Seattle, United States: Institute for Health Metrics and Evaluation (IHME).

Griliches, Z., 1969. Capital-skill complementarity. Rev. Econ. Stat. 51 (4), 465–468.

Grossmann, V., Steger, T., Trimborn, T., 2013. Dynamically optimal R&D subsidization. J. Econ. Dyn. Control 37 (3), 516–534.

Hall, R.E., Jones, C.I., 1999. Why do some countries produce so much more output per worker than others? Quart. J. Econ. 114 (1), 83–116.

Heckman, J.J., Lochner, L.J., Todd, P.E., 2006. Earnings functions, rates of return and treatment effects: The Mincer equation and beyond. In: Handbook of the Economics of Education. 1. North Holland, Amsterdam, Netherlands, pp. 307–458.

Institute for Health Metrics and Evaluation, 2013. India global burden of disease study 2010 (GBD 2010) results 1990–2010. Institute for Health Metrics and Evaluation, Seattle Technical report.

International Diabetes Federation, 2015. IDF diabetes atlas – seventh ed. URL:http://www.diabetesatlas.org.

International Labour Organization, 2015. Labour force by sex and age (thousands) Geneva. International Labour Organization, Switzerland.

Islam, N., 1995. Growth empirics: a panel data approach. Quart. J. Econ. 110 (4), 1127–1170.

Jäckle, R., Himmler, O., 2010. Health and wages: panel data estimates considering selection and endogeneity. J. Hum. Resour. 45 (2), 364–406.

Jäger, S., 2016. How Substitutable Are Workers? Evidence from Worker Deaths. Mimeo, Url:https://scholar.harvard.edu/files/jaeger/files/jmpsimon.pdf.

Jones, A.M., Rice, N., Roberts, J., 2010. Sick of work or too sick to work? Evidence on self-reported health shocks and early retirement from the BHPS. Econ. Model. 27 (4), 866–880.

Jones, C.I., 1995. R&D-based models of economic growth. J. Political Econ. 103 (4), 759–784.

Kearney, P.M., Whelton, M., Reynolds, K., Muntner, P., Whelton, P.K., He, J., 2005. Global burden of hypertension: analysis of worldwide data. Lancet 365 (9455), 217–223 ISSN 0140-6736.

Kim, S.-G., Hahm, M.-I., Choi, K.-S., Seung, N.-Y., Shin, H.-R., Park, E.-C., 2008. The economic burden of cancer in Korea in 2002. Eur. J. Cancer Care 17 (2), 136–144.

Krusell, P., Ohanian, L.E., Ríos-Rull, J.-V., Violante, G.L., 2000. Capital-skill complementarity and inequality: a macroeconomic analysis. Econometrica 68 (5), 1029–1053.

Kuhn, M., Prettner, K., 2016. Growth and welfare effects of health care in knowledge-based economies. J. Health Econ. 46 (A), 100–119.

Kuhn, M., Wrzaczek, S., Feichtinger, G., Prskawetz, A., 2015. Optimal choice of health and retirement in a life-cycle model. J. Econ. Theory 158 (A), 186–212.

Lakdawalla, D.N., Sun, E.C., Jena, A.B., Reyes, C.M., Goldman, D.P., Philipson, T.J., 2010. An economic evaluation of the war on cancer. J. Health Econ. 29 (3), 333–346.

Lim, S., Kim, H., Nam, C., Chang, H., Jang, Y.-H., Kim, S., Kang, H.-Y., 2009. Socioeconomic costs of stroke in Korea: estimated from the Korea national health insurance claims database. J. Prev. Med. Public Health 42 (4), 251–260.

Lindeboom, M., Kerkhofs, M., 2009. Health and work of the elderly: subjective health measures, reporting errors and endogeneity in the relationship between health and work. J. Appl. Econom. 24 (6), 1024–1046.

López-Casasnovas, G., Rivera, B., Currais, L., 2005. Health and Economic Growth: Findings and Policy Implications. MIT Press, Cambridge.

Lozano, R., Wang, H., Foreman, K.J., Rajaratnam, J.K., Naghavi, M., Marcus, J.R., Dwyer-Lindgren, L., Lofgren, K.T., Phillips, D., Atkinson, C., 2011. Progress towards millennium development goals 4 and 5 on maternal and child mortality: an updated systematic analysis. Lancet 378 (9797), 1139–1165.

Luca, D.L., Iversen, J.H., Lubet, A.S., Mitgang, E., Onarheim, K.H., Prettner, K., Bloom, D.E., 2018. Benefits and Costs of the Women's Health Targets for the Post-2015 Development Agenda. In: Lomborg, B. (Ed.), Prioritizing Development: A Cost Benefit Analysis of the United Nations' Sustainable Development Goals. Cambridge University Press, Cambridge, UK, pp. 244–254.

Lucas, R.E., 1988. On the mechanics of economic development. J. Monetary Econ. 22 (1),

3–42.
McGarry, K., 2004. Health and retirement: do changes in health affect retirement expectations? J. Hum. Resour. 39 (3), 624–648.
Mincer, J.A., 1974. Schooling and earnings. In: Schooling, Experience, and Earnings. NBER, New York, pp. 41–63.
Murphy, K.M., Topel, R.H., 2006. The value of health and longevity. J. Political Econ. 114 (5), 871–904.
Murray, C.J., Vos, T., Lozano, R., Naghavi, M., Flaxman, A.D., Michaud, C., Ezzati, M., Shibuya, K., Salomon, J.A., Abdalla, S., 2013. Disability-adjusted life years (DALYs) for 291 diseases and injuries in 21 regions, 1990–2010: a systematic analysis for the global burden of disease study 2010. Lancet 380 (9859), 2197–2223.
Nishimura, S., Zaher, C., 2004. Cost impact of COPD in Japan: opportunities and challenges? Respirology 9 (4), 466–473.
Feenstra, R.C., Inklaar, R., Timmer, M.P., 2015. The next generation of the penn world table. Am. Econ. Rev. 105 (10), 3150–3182. URL:https://www.rug.nl/ggdc/productivity/pwt/ [Accessed on 09/03/2018].
Prettner, K., Canning, D., 2014. Increasing life expectancy and optimal retirement in general equilibrium. Econ. Theor. 56 (1), 191–217.
Pritchett, L., Summers, L.H., 1996. Wealthier is healthier. J. Hum. Resour. 34 (1), 841–868.
Psacharopoulos, G., Patrinos, H.A., 2018. Returns to investment in education: a decennial review of the global literature. Educ. Econ. 26 (5), 445–458.
Ramsey, F.P., 1928. A mathematical theory of saving. Econ. J. 38 (152), 543–559.
Rice, D.P., 2000. Cost of illness studies: what is good about them? Injury Prevention 6 (3), 177–179.
Sala-i-Martin, X., 1997. I just ran two million regressions. Am. Econ. Rev. 87 (2), 178–183.
Sala-i-Martin, X., Doppelhofer, G., Miller, R.I., 2004. Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE) approach. Am. Econ. Rev. 94 (4), 813.
Solow, R.M., 1956. A contribution to the theory of economic growth. Quart. J. Econ. 70 (1), 65–94.
Suhrcke, M., Urban, D., 2010. Are cardiovascular diseases bad for economic growth? Health Econ. 19 (12), 1478–1496.
Viscusi, W.K., Aldy, J.E., 2003. The value of a statistical life: a critical review of market estimates throughout the world. J. Risk Uncertainty 27 (1), 5–76.
Weil, D.N., 2007. Accounting for the effect of health on economic growth. Quart. J. Econ. 122 (3), 1265–1306.
Weil, D.N., 2014. Health and economic growth. In: The Handbook of Economic Growth, vol. 2 North Holland, Amsterdam, Netherlands.
World Bank, 2015. World development indicators, 2015.http://data.worldbank.org/indicatorID-57.
World Bank, 2017. Global economic prospects, January 2017 weak investment in uncertain times. World Bank, Washington, DC.
World Health Organization, 2009. WHO guide to identifying the economic consequences of disease and injury. World Health Organization, Geneva.