Artículo Especial VOL. 2 NO 1

A preliminary model for the impact of Research and development in health care expenditure: the case of Costa Rica

Modelo preliminar para la estimación del impacto de la Investigación y el Desarrollo en los gastos de atención de la salud: el caso de Costa Rica

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ABSTRACT

This paper describes a simple model for estimating costs in the National Health System in Costa Rica that includes technology-related lag. Model parameters are associated to the system (technical lag, specialist lag and medication lag) and to the patient (severity of illness). Preliminary results suggest that (1) the model follows a GDP estimate within a 1.65% error in a simulated period of 11 years, (2) the model is accurate in accounting for the cost of attention in health services and (3) proposed R&D interventions that concentrate on solving problems related to critical parameters do have a significant effect on final national budget estimates under the assumptions of this model.

Keywords: Health Care Costs, Research and Development, Costa Rica (*source: MeSH NLM*)

1. INTRODUCCIÓN

Health expenditure is a common concern in nation States with respect to the question regarding its main drivers (1). Several factors are deemed as responsible for the observed growth of the cost, such as ageing (2), the insurance market dynamics (3), taxation (4), service quality (5), as well as individual national financial possibilities (6). The challenge in matching predictions and observed trends in health expenditure leads to a situation qualified as a black box (7).

Health care costs have been studied from the R&D point of view: return on investment of innovation in health-related market activities (e.g. (8, 9, 10)) and the social cost of particular diseases (e.g. (11, 12, 13, 14, 15)). It is clear From the public perspective, health care expenditure growth (rather than firm productivity) is key for defining national budgets while allocating funds for R&D [18, 19], in particular for Costa Rica and Latin America (20). An efficiency-oriented model (21, 22), with an emphasis on systemic failures (i.e. lags) that can be mitigated by publicly-funded R&D projects is required, under the assumption of proper execution.

This paper shows that a simple-yet-descriptive model for designing and prototyping expenditure contention measures is viable and asymptotically accurate. This research has deeper implications for system approaches for systemic cost containment in health care (23).

2. THE RESEARCH & DEVELOPMENT-RELATED LAG COST MODEL

The core problem is finding an explanatory model capable of quantifying the impact of targeted R&D in health care expenditure growth at the national expenditure level. It must allow comparison of different alternative interventions with respect to a baseline estimated from macroeconomic variables such as annual inflation rates.

The additive perspective of public costs vs. productivity

Productivity growth models that include knowledge and R&D mostly look at calculating total productivity factors (TPF) basis (24, 25, 26). The latter assumes a production function and a cost function from observables that are available and can be estimated within reasonable accuracy. In that sense, this work does not follow usual discussions such as in (27).

Cost models related to public expenditure are often posed in a rather additive tone, than the usual product of powers of different factors (28, 29, 30, 31, 32, 33, 34). The expression of *lag* or inefficiency as a power law is well established in the practices of modeling in economics (35, 36), specially while dealing with systemic factors (37).

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Recibido: 08-03-2016 Aprobado: 14-03-2016

Citar como: Núñez-Corrales S. A preliminary model for the impact of Research and development in health care expenditure: the case of Costa Rica. Rev Hisp Cienc Salud. 2016;2(1): 52-61

Considering that modeling exercises in public expenditure growth aim at creating interventions that measurably lead to lower public costs. The latter requires quantitative comparison between the output in *if-else* cases with possibiity of refutation experiments via counterfactuals (38, 39, 40). In the case of public health care expenditures, our discussions follows (41) closely in the details.

Cost and lag factors

Health care cost factors are a widely discussed topic (7). The model considers two particular types in line with the previous discussion: direct cost factors and lag factors. Direct costs include four variables: cost of health technicians (T) and physicians (P) (42), cost of medications (M) (43) and patient recurrence (R) (44). It is clear that T, P and M are system-related factors and R is patient-related.

With respect to lag factors, the model considers four of them as well (45). Technical lag (α) describes the conjunction of elements lacking sufficient technical bandwidth or quality as for being useful. Physician lag (β) refers to limitations in medical care at the specialist level explained by lack of training, poor or no access to adequate diagnosis and attention tools or facilities and other exogenous conditions [46]. Medication lag (γ) is explained by several sub-factors, including lack of patient adherence, undesirable interactions and incorrect medication (47). Finally, a recurrence lag (λ) can be explained as the effect that disease severity exerts upon potentially multiple visits and general cost of attention (48).

Having in mind the public nature of the health system in Costa Rica (including insurance an other additional costs) as well as the need for a simplified model departing from measured or well-estimated data, additional core factors have been left aside.

Description of the model

The proposed model departs *ab initio*. The cost function assumes that total health care cost *per capita* is described by the sum of each system-related factor (having the appropriate lag exponent) multiplied by the average amount of visits per patient per year; the latter product is modulated by the recurrence lag exponent. Then, the cost X is given by

$$X = [R \cdot (T^{\alpha} + P^{\beta} + M^{\gamma})]^{\lambda}$$

Lag exponents must obey $\alpha,\beta,\gamma,\lambda \geq 1$. Since the application interest of the model is that of estimating the impact of R&D measures over inefficiencies (that is, lowering the values of the exponents), the factors are estimated per year according to measurements in the national health system. It is clear that the case $\alpha,\beta,\gamma,\lambda = 1$ refers to optimal operation under available resources.

Input data

Three primary sources of information going back to 2011 were used. The choice of year was dependent on the most recent source of information from the Ministry of Health, required for the GDP-based estimates (49). Estimates for demographic growth were obtained from the most recent report of the National Institute of Statistics and Census [50]. Table 1 summarizes the values for each factor based on (51). Costs are given in dollars but were originally calculated in colones at a exchange rate of 539.75 colones per dollar (2015-08-26) (52). All conversions are done at present value. Professional time estimates were updated based on average salary increases from 2011 to 2015 assuming the values hold until 2021.

Table 1: Input data for the health care lag cost model at 2011.

Factor	Value
T	$ 9.26
P	$ 34.74
M	$ 27.79
R	2

Regarding estimates of lag exponents, there is extensive literature describing the problem and associated challenges (e.g. (53, 54, 55, 56, 57)). Results presented in this work used maximum likelihood methods (58, 59), where transformations were applied to available data on disease severity and, in the case of medication lag, a 30% of ineffectiveness was assumed.

Transformation of severity and medication lag to power law form proceeded by taking into account both potentially many factors [60] as well as necessary care in evaluating the impact of the distribution of disease severity [61]. Table 2 summarizes final values used in the model. Population data and estimations are given by Table 3.

Table 2: Input data for the health care lag exponents.

Factor	Value
α	1.09
β	1.07
γ	1.16
λ	1.03

Table 3: Input data for population estimations.

Year	Population
2011	4592149.00
2012	4652458,93
2013	4713168,14
2014	4773129,93
2015	4832233,81
2016	4890379,45
2017	4947489,59
2018	5003401,96
2019	5058007,15
2020	5111238,22
2021	5163037,97

Proposed measures

With the aim of testing the model, nine R&D interventions were proposed with a proposed value of $2,000,000.00 each. Subtractive exponents were estimated by establishing lower bounds for available national data in the respective power laws [62]. Measures were classified as structural (technical and infrastructure elements, STR), clinical (physicianrelated, CNC), biomedical (medications and pharmacology, BMD) and cultural (prevention CLT) in agreement with a modern view of public health improvement [63]. Interventions are described as follows.

- **Electronic health records (EHR) (**$\alpha = -0.03$**)** Digitizing health information reduces human errors, provides continuity on patient evolution and allows for integrated policies and actions [64].
- **Fast and accurate prognosis (FAP) (**$\alpha = -0.018$**)** The ability to rapidly determine factors contributing to explain health state of patients is critical for and adequate attention in future clinical steps [65].
- **Ambient-assistive technologies (AAT) (**$\alpha = -0.01$**)** The utilization of several devices, procedures and mechanisms based improved by technological means reduces repetition and error, as well as reduces operational costs [66].
- **Biomedical and clinical research programs (BRP) (**$\beta = -0.002$**)** The endogenous ability to develop biomedical research in critical diseases improves knowledge of physicians and leads to better clinical facilities [67, 68, 69].
- **Health monitoring and Big Data (HMB) (**$\beta = -0.007$**)** The increasing acquisition of smartphones by patients, a widening range of sensors and health monitoring devices as well as trends in Big Data provide opportunities for integrating personal data through algorithms that lead to clinical discoveries under clear ethical guidelines [70, 71, 72, 73].
- **Automated drug incompatibility discovery (ADD) (**$\gamma = -0.002$**)** The ability to record patient-drug and drug-drug incompatibilities largely diminishes severity of cases, additional misplaced costs and pharmacological ineffectiveness [74, 75, 76].
- **Prescription adherence apps (PAA) (**$\gamma = -0.003$**)** The increasing availability of smartphones in the general public facilitates the development of software applications (i.e. apps) that help patients adhere strictly to their prescriptions, leading to higher rates of effectiveness and less unused medications [77].
- **Research and technology for improved nutrition (RIN) (**$\lambda = -0.003$**)** Nutrition is at the base of improving health, which can be aided by proper research and technology developments towards improved food related habits [78].
- **Technology for early self-diagnose (ESD) (**$\lambda = -0.0005$**)** As health culture strengthens and technology becomes available, a series of research results suggest a radical change in the amount and variety of proactive, preventive measures patients can take in advance. [79, 80].

Assumptions and limitations

The model is limited by definition in considering only three system-related factors and one-patient related factor. Also, no measure includes lowering factor costs. This exercise assumes that one patient has access to two technicians, two physicians and one medication per medical appointment [51]. Finally, lag exponents remain constant for the whole simulated period and supposed to be statistically observable.

RESULTS

The model was utilized for an economic simulation scenario spanning from 2011 to 2021 using two equations for the expected value of health care expenditure. X as described above estimates health cost per capita. The analysis starts at studying the behavior of X against another stable predictor based on known GDP per capita expenses and average expected inflation rates. Then, individual measures are contrasted as well as grouped into classes. Finally, the effects are computed and contrasted against expected values of the GDP-based **model in order to contrast alternative histories of health care expense where lower costs can be understood as positive lagged responses [81].**

Deviation from GDP per capita estimates

Let X_1 be the initial value for annual per capita cost in the series given by the equation

$$X_1 = [R \cdot (T_1^{\alpha} + P_1^{\beta} + M_1^{\gamma})]^{\lambda} \tag{2}$$

where R remain fixed for all future costs. Supposing that an annual inflation rate i_F applies to all factors T_1,P_1 and M_1 and no other market force changes their response, the value at year n of the variable factors becomes

$$T_n = (1 + i_F)^{n-1} T_1 \tag{3}$$

$$P_n = (1 + i_F)^{n-1} P_1 \tag{4}$$

$$M_n = (1 + i_F)^{n-1} M_1 \tag{5}$$

Correspondingly,

$$X_n = [R \cdot ((1 + i_F)^{\alpha \cdot (n-1)} T_1^{\alpha} + (1 + i_F)^{\beta \cdot (n-1)} P_1^{\beta} + (1 + i_F)^{\gamma \cdot (n-1)} M_1^{\gamma})]^{\lambda} \tag{6}$$

Let

$$T' = \left(\frac{T_1}{1 + i_F}\right)^{\alpha} \tag{7}$$

$$P' = \left(\frac{P_1}{1 + i_F}\right)^{\beta} \tag{8}$$

$$M' = \left(\frac{M_1}{1 + i_F}\right)^{\gamma} \tag{9}$$

(10)

and then, after substituting Eqs. 7–9 into Eq. 6, X_n becomes

$$X_n = [R \cdot ((1 + i_F)^{\alpha n} T^0 + (1 + i_F)^{\beta n} P^0 + (1 + i_F)^{\gamma n} M^0)]^{\lambda} \tag{11}$$

For matters of simplicity, let $\pi = \max\{\alpha,\beta,\gamma\}$ and $W = 3 \cdot \max\{T^0, P^0, M^0\}$ describe a case of equal (and, in this case, maximum) factor cost and factor lag. Then

$$X_n \leq (RW)^{\lambda} \cdot (1 + i_F)^{(\lambda\pi) \cdot n} \tag{12}$$

indicates that in a worst case scenario, expenditure is driven by patient recurrence and factor cost increased exponentially by disease severity multiplied by the compound interest rate powered by both factor lags and disease severity.

In order to provide a fair comparison, another expenditure estimator which agrees with data needs to be defined. Let B_1 be the measurement for year one, only affected by national annual inflation rate i_N. Then the estimator B_n becomes

$$B_n = (1 + i_N)^{n-1} B_1 \tag{13}$$

For the following analysis and without loss of generality $\exists n_0 | B_n < X_n, \forall n > n_0$ is assumed. Then the ratio

$$\frac{X_n}{B_n} \leq \frac{(1 + i_N)(RW)^{\lambda}}{B_1} \cdot \left[\frac{(1 + i_F)^{(\lambda\pi)}}{(1 + i_N)}\right]^n \tag{14}$$

gives the difference ratio between both estimators. Back to theoretical considerations, it is reasonable for factor inflation rates to be a fraction of national inflation rates, mostly due to the fact that the latter contribute to the former [82], thus $i_F < i_N$. If it is also the case that $(1 + i_F)^{(\lambda\pi)} < (1 + i_N)$, then $X_n/B_n \rightarrow 0$ asymptotically when $n \rightarrow \infty$. It is not hard to see that most cases of interest fall into this trend.

In the following analysis, the percentage difference $_n$ was calculated as

$$\epsilon_n = 100 \cdot \frac{X_n - B_n}{B_n} \tag{15}$$

Considering that, according with the previous discussion, the upper bound was found for a general case where equality holds, the value of X_n/B_n is actually lower, which reflects in the asymptotic behavior of $_n$ (Fig. 1). In order to ensure further realism, final figures were scaled by population data.

Effects of interventions

Having calculated the percentage difference for X_n vs B_n, it is now necessary to estimate the effects of applying different measures. First, total savings in health care expenditure were estimated 2. Data suggest preventive interventions related to nutrition (RIN) have the strongest expected effect in total and in time. When grouped into classes, the highest savings come from cultural (CLT) and structural (STR) interventions (Fig. 3).

Finally, when all interventions are added in, savings in health care expenditure become evident (Fig. 4). In general, an interesting observation is that Y , the intervention-adjusted version of X, reaches a value in 2021 similar to that of 2017 for the unadjusted estimate. Numerically, estimated accumulated savings from all interventions in the period 2011-2021 are over \$6000M.

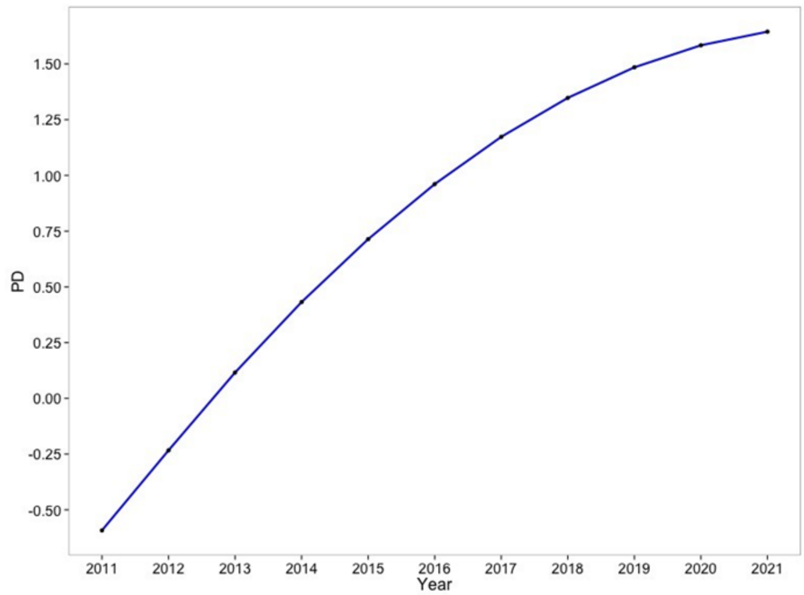

Figure 1: Behaviour of the percentage difference $_n$.

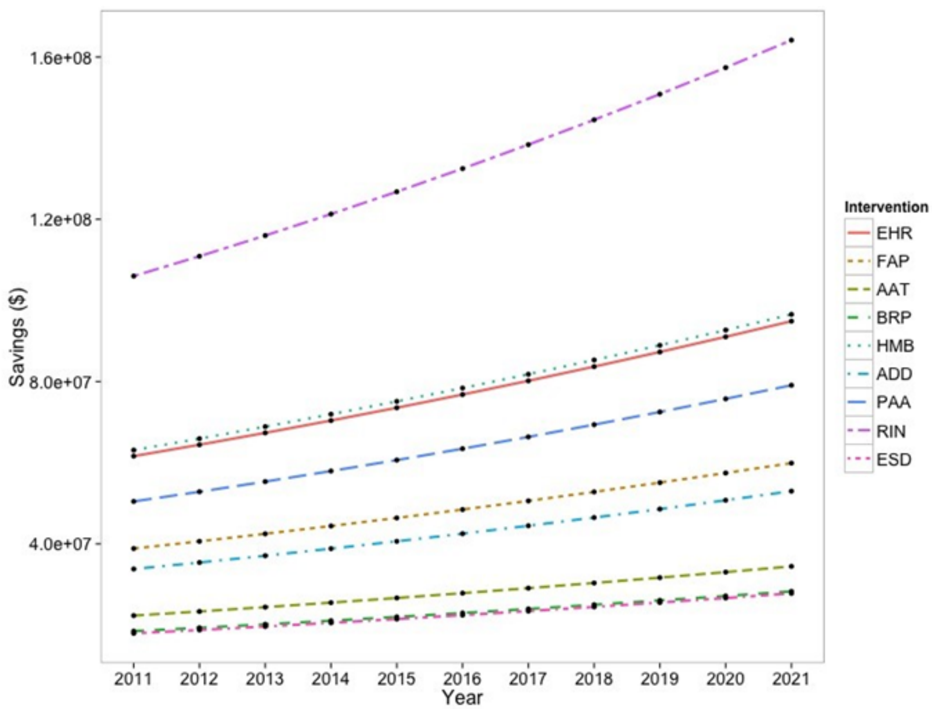

Figure 2: Savings for each individual intervention.

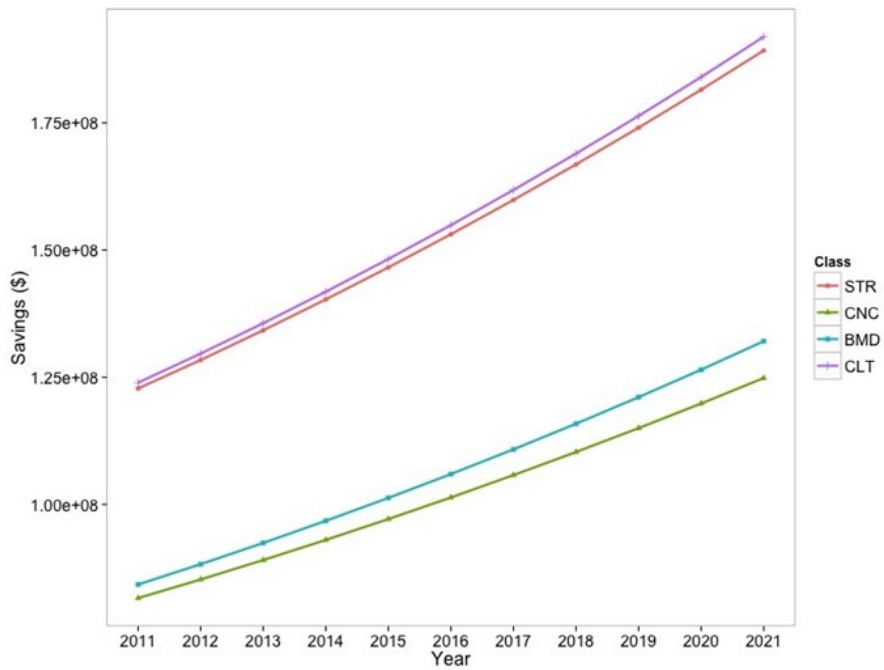

Figure 3: Savings for each class of intervention.

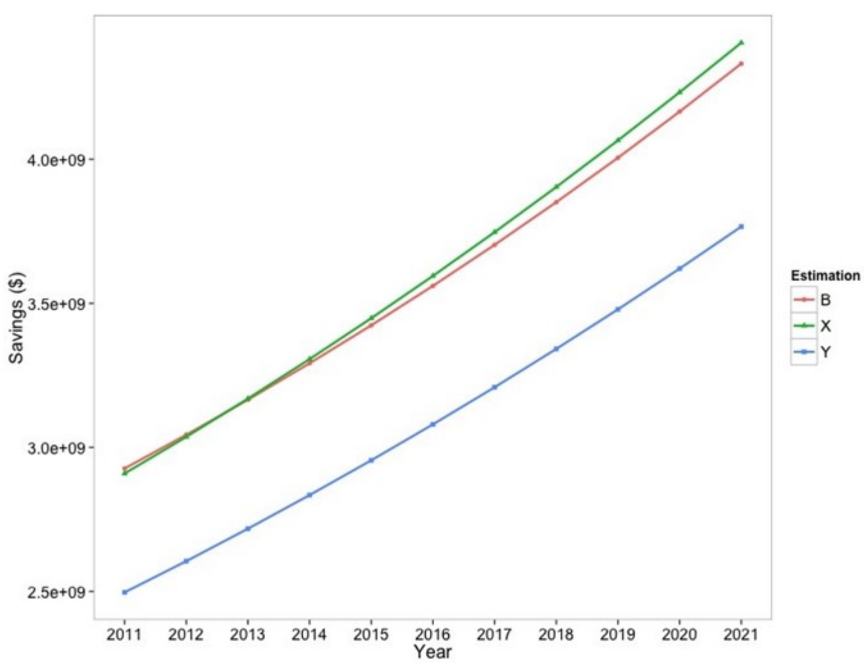

Figure 4: Total savings in heath care expenditure. *Y* is the adjusted version of *X* by applying all proposed measures.

DISCUSSION

The model presented in this paper, according to preliminary evaluation using a case scenario, seems to yield reasonable estimations that agree with macroeconomic variables. The results also suggest that the effect of R&D interventions can be captured appropriately by power laws within an additive framework.

If the results of the model are valid, then R&D interventions are critical for lowering actual health care expenditures despite their initial development and scaling costs. The main cause of systemic inefficiencies is two-fold: first, the lack of mechanisms leading to minimization of error, early prognosis and increased information traffic lead to high degrees of repetition; and second, any improvements on disease severity have profound impacts, even more noticeable than any other interventions.

From the point of view of national finances, budget definition in relation to R&D is not an easy task when no decision mechanisms are available, in particular because of the inherent difficulty in foresight. Modeling, in more and better forms than the current one presented in this paper, is central to anticipating possible effects based on numerically computing the expected consequences that interventions might have. This preliminary exercise shows that R&D investments hold a very large, positive cost/benefit relation, one that translates (if well focused) into expenditure savings many orders of magnitude higher that the expenditure on R&D.

ACKNOWLEDGEMENTS

The author wishes to acknowledge constant support by the Ministry of Science, Technology and Communications, as well as the facilitation of data from the Ministry of Health in Costa Rica. This work was performed under the yearly National Budget Funding allocation of the Republic of Costa Rica.

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ISSN: 2215–4248

Revista Hispanoamericana de Ciencias de la Salud