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ORIGINAL PAPER

Testing the Grossman model of medical spending determinants with macroeconomic panel data

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Abstract
Michael Grossman's human capital model of the demand for health has been argued to be one of the major achievements in theoretical health economics. Attempts to test this model empirically have been sparse, however, and with mixed results. These attempts so far relied on using—mostly cross-sectional—micro data from household surveys. For the first time in the literature, we bring in macroeconomic panel data for 29 OECD countries over the period 1970–2010 to test the model. To check the robustness of the results for the determinants of medical spending identified by the model, we include additional covariates in an extreme bounds analysis (EBA) framework. The preferred model specifications (including the robust covariates) do not lend much empirical support to the Grossman model. This is in line with the mixed results of earlier studies.

Keywords Medical spending · Grossman model · Extreme bounds analysis · OECD panel

JEL Classification C12 · C23 · I10 · I12

Introduction

The share of health care expenditure in Gross Domestic Product (GDP) is rising in virtually all rich countries, with the rise being most pronounced in the United States. According to OECD data, the health care expenditure share in GDP has more than tripled in the US between 1960 and 2010 from around 5% to almost 18%, while over the same period that share has approximately doubled in other rich countries. As a large percentage of health care expenditures in rich countries is borne by the public sector, their surge has turned into one of the central fiscal challenges facing the developed world. It is therefore of paramount importance to understand the causes of the continuing rise in health care expenditure in OECD countries.

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However, the research into the determinants of health care expenditure (growth) since the pioneering study by Newhouse [40] has for a long time failed to disclose robust explanatory variables beyond national income growth (see [45]). Conceivable expenditure drivers were tested on an ad hoc basis without much theoretical groundwork. Still, one micro-founded theoretical model for the demand for medical care—and hence for medical spending—exists: the seminal Grossman [21, 22] model. This model goes beyond explaining the demand for medical care to cover the demand for health in general. Drawing on the household production theory by Becker [3], the model posits that individuals facing a depreciating human capital stock in the form of health as they grow older use medical care and their own time to (re-)produce health capital. Investment in health production will be optimal when the marginal cost of health production equals the marginal benefits of the improved health status in the form of 'healthy time'. Health status affects household utility directly—the so-called 'pure consumption' effect—and indirectly in that more 'healthy time' translates into higher labor income: the 'pure investment' effect.

Following Grossman's [21] lead to validate his model empirically, a number of contributions have used micro data from household surveys to test it [8, 15, 17, 18, 34, 41, 57, 58]. The results were mixed, to say the least. Most papers

have found signs on the coefficients of certain explanatory variables that were not in line with the model's theoretical predictions, prompting Zweifel and Breyer [60] and Zweifel [59] to conclude that the Grossman model is—at least in parts—rejected by the data. Unsurprisingly, Grossman [23] disagrees, pointing out (among other things) that the model's predictions for the signs on the coefficients are not always clear-cut.

As the preceding paragraph suggests, not much progress has been made in terms of testing the model since Grossman provided his comprehensive review in the *Handbook of Health Economics* in 2000. To get out of the doldrums, we propose a new approach to testing the Grossman model that consists in using macroeconomic panel data and checking the robustness of the results by means of extreme bounds analysis (EBA). Given that the call for 'microfoundations' of macroeconomics is almost as old as the Grossman model, it is surprising that the literature in this field has not yet moved from testing that model of household behavior with micro data to testing it also with macroeconomic data. Outside health economics, macroeconomists have attempted to build on microeconomic models of household behavior to derive relationships between macroeconomic variables since the 1970s. To justify this, it is usually assumed that individual preferences can be aggregated in such a way that society can be treated as if it consists of a single 'representative agent'. If the Grossman model correctly describes individual behavior, its predictions should also be valid for the behavior of the 'representative agent' and should hence be reflected in macroeconomic data.

Of course, we are aware that the representative agent assumption is far-fetched. Sonnenschein [49, 50], Mantel [36], and Debreu [11], for instance, have shown that even if the behavior of all individuals satisfies microeconomic restrictions, the aggregate usually fails to reflect those properties. Nonetheless, Krusell and Smith [32] argue that 'approximate aggregation' is feasible even with heterogeneous agents, which leads to time series for aggregates that are often almost identical to those generated by the corresponding representative agent models. This changes, however, when income inequality and borrowing constraints for low-income households are introduced (ibid: 328). This is relevant in our context because of shifts in the income distribution over time in OECD countries. Finally, several of the countries in our panel have a national health service modeled after the NHS of the United Kingdom. Its budget and hence aggregate medical spending is determined by politicians rather than individuals. Applying the Grossman model to these countries is hard to justify. Despite these considerations, we still believe that it is interesting to know whether the Grossman model's predictions for what determines individual demand for medical care are reflected in macroeconomic data. Extending earlier work that focuses on explaining the surge in health care expenditure [25–27], we here concentrate on testing the predictions of the Grossman model for the demand for medical care, leaving aside its predictions for the demand for health.[1] The reason is that macro data from the OECD for the variables used in household-survey-based studies as proxies for the individuals' health, e.g., the self-perceived health status or the number of working days lost due to illness, are available for only a very limited number of countries and/or years. Long time series for health care expenditure, on the other hand—the variable used by Grossman [21] to measure the demand for medical care—are abundant.

Besides testing the statistical significance of the variables identified by the Grossman model as determinants of medical spending, we also aim at testing the robustness of these drivers. To this end, we use an innovative econometric technique known as extreme bounds analysis (EBA). It avoids ad hocery by including *all* variables in the analysis that have been suggested as determinants in a certain field of research to find out whether the results regarding our key variables are sensitive to changing the set of controls. EBA has originally been applied to the field of economic growth (see [35, 47, 55]), where—much like in the field of medical spending—a large number of potential determinants has been suggested by the literature. EBA has since spread to fields of research other than economic growth (see [13, 14, 16, 39, 53]). Hartwig and Sturm [27] used EBA to test the robustness of some 50 drivers of health care expenditure growth that had been suggested in the literature. Here, we will use the same technique and these drivers to test the robustness of the determinants suggested by the Grossman model. The advantage of using EBA as robustness test means that "when a variable is declared robust, it would have been tested over tens of thousands of times before that conclusion is drawn" [5].

The remainder of this paper is structured as follows. The next section sketches the Grossman model. Section 3 discusses our dataset, and Sect. 4 explains the methodology of Extreme Bound Analysis. Section 5 presents the results. Section 6 concludes.

The Grossman model

In the model, individuals are assumed to derive utility from consuming a commodity (Z) and disutility from 'sick time' (t^s), which is a function of their stock of health capital H_t, according to the inter-temporal utility function (1):

$$\int_0^T e^{-\rho t} U\left[t^s\left(H_t\right), Z_t\right], \tag{1}$$

[1] Cropper [8], Gerdtham et al. [18] and Gerdtham and Johannesson [17] did the opposite, testing only the demand for health sub-model.

with $\partial U_t/\partial t^s < 0, \quad \partial U_t/\partial Z_t > 0, \partial t^s/\partial H_t < 0$ and ρ a time discount factor.

The dynamics of H are given by Eq. (2)

$$\dot{H}_t = I_t\left(M_t, t^i\right) - \delta_t H_t, \tag{2}$$

with $\partial I_t/\partial M_t > 0, \quad \partial I_t/\partial t^i > 0$. This means that investment in health capital I is produced by medical care M and own time spent, for instance, on sporting activities (t^i). On the other hand, health capital depreciates at a rate δ. In Grossman's formulation, δ depends only on the individual's age (t_i) and is hence exogenous, but others have made δ endogenous by adding lifestyle variables like tobacco and alcohol intake [18], or pollution [15] and unemployment [17]. The covariates we will include in our EBA regressions can be thought of as acting on the depreciation rate as in these contributions.[2]

Asset accumulation is given by Eq. (3)

$$\dot{A}_t = rA_t + Y\left[t^s\left(H_t\right)\right] - \pi_t^H I_t - \pi_t^Z Z_t, \tag{3}$$

where A is the stock of financial assets, r is the rate of interest, Y is the earned income as a function of 'sick time', and π^H and π^Z are the marginal (and average) cost of investment in health and consumption, respectively. The boundary conditions are $H(0) = H_0$, $A(0) = A_0$, $H_t \geq H'$ and $A_t \geq 0$, where H' is the 'death stock' of health capital.

The individual has to solve the control problem to choose the time paths for H_t and Z_t that maximize the inter-temporal utility function (1) subject to the dynamic constraints (2) and (3) and the boundary conditions. The solution for this problem is given by Eq. (4)[3]

$$\left\{\frac{\partial U_t/\partial t^s}{\lambda(0)}e^{-(\rho-r)t} + \frac{\partial Y_t}{\partial t^s}\right\}\frac{\partial t^s}{\partial H_t} = \left\{r + \delta_t - \frac{\dot{\pi}_t^H}{\pi_t^H}\right\}\pi_t^H, \tag{4}$$

where $\lambda(0)$ is the shadow price of initial assets.

Equation (4) states that the marginal benefit of additional health capital on the left-hand side must be equal to the marginal cost of holding it on the right-hand side. Additional health capital reduces 'sick time', which provides direct utility (the first summand on the left-hand side representing the 'pure consumption' effect) in addition to increasing labor income (the second summand representing the 'pure investment' effect). A rise in the depreciation rate δ raises the marginal cost of investing in health capital. So does a rise in the interest rate because opportunity cost increases. On the other hand, if health capital rises in value in the future ($\dot{\pi}_t^H > 0$), this lowers the relative cost of investing today.

Equation (4) is the centerpiece of the Grossman model. However, in the empirical literature starting with Grossman [21] it is not Eq. (4) that is tested. Instead, the model is split into a 'pure consumption' (PC) sub-model in which the term $\frac{\partial Y_t}{\partial t^s}\frac{\partial t^s}{\partial H_t}$ on the left-hand side of Eq. (4) is set to zero and a 'pure investment' (PI) sub-model in which the term $\frac{\partial U_t/\partial t^s}{\lambda(0)}e^{-(\rho-r)t}\frac{\partial t^s}{\partial H_t}$ is dropped. Grossman [23] argues that this is necessary because it "is difficult to obtain sharp predictions concerning the effects of changes in exogenous variables in a mixed model in which the stock of health yields both investment and consumption benefits". Also, he thinks that the monetary returns are large relative to the 'psychic' returns and therefore focusses on the PI model.[4] The latter is derived from Eq. (4) by dropping the first term on the left-hand side and taking logs:

$$\ln\left[-\partial t^s/\partial H_t\right] + \ln w_t = \ln\delta_t + \ln\pi_t^H - \ln\psi_t, \tag{5}$$

where the nominal wage rate w_t equals $-\frac{\partial Y_t}{\partial t^s}$, and $\psi_t = \delta_t/\left[r + \delta_t - \frac{\dot{\pi}_t^H}{\pi_t^H}\right]$.

The PC model is derived from Eq. (4) by dropping the second term on the left-hand side and taking logs:

$$\ln\left[\frac{\partial U_t}{\partial t^s}\frac{\partial t^s}{\partial H_t}\right] - \ln\lambda(0) - (\rho - r)t = \ln\delta_t + \ln\pi_t^H - \ln\psi_t. \tag{6}$$

[2] Strulik [51] criticizes Eq. (2) for implying that the loss of health capital through depreciation is an increasing function of its stock. This means that people lose health fast when they are healthy and that the loss of health slows down as health deteriorates. "This creates an equilibrating force that allows individuals to use health investments to converge towards a fixed point of constant health" [51]. Since convergence towards constant health, i.e., immortality is a troubling prediction, Dalgaard and Strulik [9] and Strulik [52] suggest to model aging differently. Drawing on Mitnitski et al. [38] and more papers by these authors, Dalgaard and Strulik adopt the perspective supported by gerontology that aging is triggered by the accumulation of health deficits and that this process of increasing frailty is a positive function of the health deficits that are already present in an individual. This turns Grossman's mechanism for individual aging upside down. Dalgaard and Strulik ([9]: 679) recognize, however, that in applications beyond individual aging, for instance as a macro representation of the law of motion of the health capital stock, Eq. (2) may be perfectly reasonable.

[3] See Nocera and Zweifel ([41], Appendix A) for a derivation. We basically follow their notation in this section, which in turn is based on Wagstaff [57].

[4] So do Cropper [8] and Erbsland et al. [15]. However, Wagstaff [57] finds "serious inconsistencies between the pure investment model and the data". Likewise, Leu and Gerfin [34] find the PI model to be rejected by their data. Combining a bell-shaped boundary of production possibilities with negatively sloped indifference curves in the healthy days-consumption space, Zweifel [59] claims that the optimum (the tangent point) "cannot lie on the increasing portion of the frontier, where more investment in health also permits to increase consumption. Rather, it necessarily lies beyond the peak, indicating a trade-off between health and consumption. This insight also casts doubt on the relevance of the popular pure investment variant of the MGM (Michael Grossman Model)".

To estimate Eqs. (5) and (6), assumptions must be made about the functional forms of $t^s(\cdot)$, $\delta(\cdot)$, $\pi^H(\cdot)$ and $U(\cdot)$. Following Grossman [21], we assume that

$$t_i^s = \beta_1 H_{it}^{-\beta_2}, \tag{7}$$

where β_1 and β_2 are positive constants and

$$\ln \delta_{it} = \ln \delta_0 + \beta_3 t_i, \tag{8}$$

with $\beta_3 > 0$. Unlike in the previous literature, where subscript i denotes the ith person, it here stands for the ith country.

Investment in health capital is assumed to be affected by combining time (t^i) and medical care (M) according to a Cobb–Douglas production function with constant returns to scale. Furthermore, Grossman assumes that education (E) raises the efficiency of the production process in the household sector. This gives rise to the investment function (9):

$$I_{it} = M_{it}^{\beta_4} t^{i^{1-\beta_4}} E_{it}^{\beta_5}, \tag{9}$$

with $0 < \beta_4 < 1$ and $\beta_5 > 0$.

Under constant returns to scale, the marginal cost of investment function (10) can be derived:

$$\ln \pi_{it}^H = \left(1 - \beta_4\right) \ln w_{it} + \beta_4 \ln P_{it}^M - \beta_5 E_{it}, \tag{10}$$

where P^M is the price of medical care and E is the education measured in years of formal schooling.

The utility function is assumed to be of the form

$$U_{it} = \beta_6 t_i^{s\beta_7} + g\left(\mathrm{Z}_{it}\right), \tag{11}$$

with $\beta_6 < 0$, $0 < \beta_7 < 1$ and where g(·) is some function.

Finally, an assumption has to be made about the term ψ_t. We follow Wagstaff [57] in assuming that

$$\psi_{it} = \beta_8 t_i, \tag{12}$$

with $\beta_8 > 0$.

Now the equations for the demand for health and for medical care can be derived. Consider first the demand for health in the PI model. From (7) it follows that

$$\frac{\partial t_i^s}{\partial H_{it}} = -\beta_1 \beta_2 H_{it}^{-\beta_2 - 1}. \tag{7'}$$

Inserting this into (5) and making use of (8), (10) and (12) yields

$$\ln H_{it} = \beta_9 + \beta_4 \varepsilon \ln w_{it} - \beta_4 \varepsilon \ln P_{it}^M - \left(\beta_3 - \beta_8\right) \varepsilon t_i + \beta_5 \varepsilon E_{it} + u_{1it}, \tag{13}$$

with $\beta_9 = \varepsilon ln \beta_1 \beta_2$ and $\varepsilon = \frac{1}{1+\beta_2}$. ε is the elasticity of the demand for health w.r.t. the marginal productivity of health capital, which Grossman also calls the elasticity of the marginal efficiency of health capital (MEC) schedule. From $\beta_2 > 0$ it follows that $0 < \varepsilon < 1$. Grossman treats the term $u_{1it} = -\varepsilon ln \delta_0$ as an error term with zero mean and constant variance.

The demand for medical care follows from Eqs. (2), (9) and the cost-minimizing condition for health investment, $\frac{P_{it}^M}{w_{it}} = \frac{\beta_4}{1-\beta_4} \frac{t_i^i}{M_{it}}$,

$$\begin{aligned} \ln \mathrm{M}_{it} &= \beta_{10} + \ln H_{it} + \left(1 - \beta_4\right) \ln w_{it} \\ &\quad - \left(1 - \beta_4\right) \ln P_{it}^M + \beta_3 t_i - \beta_5 E_{it} + u_{2it}, \end{aligned} \tag{14}$$

with $\beta_{10} = -\left(1 - \beta_4\right) ln\left[(1 - \beta_4)/\beta_4\right]$ and $u_{2it} = ln\delta_0 + ln\left[1 + \frac{H_{it}}{H_{it}\delta_{it}}\right]$. Wagstaff [57] treats u_{2it} as an error term.

The stock of health capital H enters the demand for medical care equation with a coefficient equal to + 1. This reflects the basic idea of the model that medical care is demanded to build up health capital. Thus, there is a positive relationship between the stock of health capital an individual has, or aims at, and his or her demand for medical care. The main critique of Zweifel et al. [61] and Zweifel [59] directed against the Grossman model is that most empirical studies found a negative relationship between health status and the demand for medical care, not a positive one. In other words, the sick demand medical care, not the healthy. If we had macroeconomic data on health status, we could test the structural demand function for medical care (14). Since, as was pointed out in the introduction, such data are not available,[5] we follow Grossman [21] in estimating the reduced form demand function for medical care, which results when Eq. (13) is inserted into Eq. (14) to yield Eq. (15)[6]

$$\begin{aligned} \ln \mathrm{M}_{it} = &\ const. + \left[\left(1 - \beta_4\right) + \varepsilon \beta_4\right] \ln w_{it} \\ &- \left[\left(1 - \beta_4\right) + \varepsilon \beta_4\right] \ln P_{it}^M + \left[\beta_3 (1 - \varepsilon) + \varepsilon \beta_8\right] t_i \\ &- \left[\beta_5 (1 - \varepsilon)\right] E_{it} + u_{1it} + u_{2it}. \end{aligned} \tag{15}$$

So the PI model identifies four determinants of the demand for medical care or health care expenditure, respectively, the nominal wage rate (w) with a positive sign, the price of medical care (P^M) with a negative sign, age (t) with a positive sign and knowledge capital/education (E) with a negative sign.[7] Furthermore, the coefficients on the wage rate and

[5] Frailty indices are emerging for a number of European OECD countries that could be used to measure the health status at the population level [24, 46]. Currently, however, not enough observations are available in the time dimension for the purpose of this paper.

[6] It should be noted that by estimating the reduced form demand function for medical care one accepts the assumption implicit in Eq. (14) that the coefficient on $\ln H_{it}$ is equal to + 1. Zweifel's conjecture that this coefficient is rather negative is thereby sidelined.

[7] The sign on education is negative because better educated individuals are hypothesized to be more efficient producers of their health, and hence need less medical care to achieve an increase in their stock of health capital.

on the price of medical care are predicted to be identical in absolute value (see [23]).

In a similar way, it is possible to show that the demand for health function in the PC model is given by

$$\begin{aligned}\ln H_{it} = \; & const. - \left(1-\beta_4\right)\gamma \ln w_{it} \\ & - \beta_4\gamma \ln P_{it}^{M} - \left[(\beta_3-\beta_8)+(\rho-r)\right]\gamma t_i \\ & + \beta_5\gamma E_{it} - \gamma \ln \lambda_i(0) + u_{3it},\end{aligned} \tag{16}$$

with $u_{3it} = -\gamma ln\delta_0$ and $\gamma = \frac{1}{1+\beta_2\beta_7}$. γ is the elasticity of demand for health capital. From $\beta_2 > 0$ and $0 < \beta_7 < 1$ it follows that $0 < \gamma < 1$.

The reduced form demand function for medical care in the PC model is found by inserting (16) in the structural demand function (14). This yields

$$\begin{aligned}\ln \mathrm{M}_{it} = \; & const. + \left[\left(1-\beta_4\right)+(1-\gamma)\right] \ln w_{it} \\ & - \left[1+\beta_4(\gamma-1)\right] \ln P_{it}^{M} \\ & + \left[\beta_3+(\beta_8-\beta_3)(r-\rho)\gamma\right] t_i \\ & - \left[(1-\gamma)\beta_5\right] E_{it} - \gamma \ln \lambda_i(0) + u_{2it} + u_{3it}.\end{aligned} \tag{17}$$

So the PC model predicts the same determinants and coefficient signs for the demand for medical care as the PI model. There are two differences; however, first, the PC model does not predict the coefficients on the wage rate and on the price of medical care to be the same in absolute value. Second, the PC model identifies an additional determinant: the shadow price of initial assets $\lambda(0)$. A high shadow price means a strongly binding wealth constraint, in other words a low stock of wealth. As the coefficient on the shadow price is negative, higher initial wealth should go along with a higher demand for medical care according to the PC model.[8]

Data

Besides testing the statistical significance of the determinants of medical spending identified by the Grossman model, we also aim at testing the robustness of these drivers in an extreme bounds analysis framework. This means that we add other potential drivers of medical spending to those identified by the Grossman model. For inclusion in our EBA, we aim at complete coverage of potential drivers that have been suggested in the literature. Gerdtham et al. [19] deliver a comprehensive list of potential determinants that were suggested prior to 1998 and Martín et al. [37] update this list based on a systematic search for literature on the determinants of health care expenditure (HCE) in medical databases and principal health economics journals over the period 1998–2007.[9]

We include in our analysis socio-demographic, economic, and technological factors as well as a number of institutional variables (mostly dummy variables) pertaining to specifics of the national health systems. For example, one of the institutional dummy variables takes the value of one for countries (and years) with fee-for-service as the dominant means of remuneration in primary care and zero otherwise. We reproduce and update these variables to the extent possible.

For the reproduction of the institutional dummy variables, we rely on the information in Gerdtham et al. [19] on how to construct them. Gerdtham et al.'s dataset covers 24 OECD countries and the time period 1970–1991. We carry forward these time series with information from Christiansen et al. [6]. They use almost the same set of explanatory variables as Gerdtham et al. [19] and give information on the institutional characteristics of health systems for the period 1980–2003. Christiansen et al. [6] investigate European Union (EU) instead of OECD countries, however. This means that for the OECD countries that are also EU members, we can in general establish time series for the institutional dummy variables that cover the period 1970–2003. For the non-EU OECD countries, however, the series end in 1991.

Finally, we use information from Paris et al. [44] to further update our data on the institutional setting. Paris et al. [44] do not report time series data; they describe the state of the national health systems for 29 OECD countries in 2009/2010. This gives us data points for the institutional dummy variables for 2009/2010. Furthermore, we assume that if the value we derive from Paris et al. for 2009/2010—0 or 1—is the same as the value for 2003 we get from Christiansen et al. [6] or the value for 1991 we get from Gerdtham et al. [19] for the non-EU OECD countries, then there has been no change in the meantime, and we close the gaps in the time series with the respective values. If the values are not the same, however, we conclude that there has been a change in the institutional setting at some unknown point

[8] Grossman suggests adding (initial) wealth to the regressors in the demand functions for medical care to discriminate between the PI and the PC model. "Computed wealth elasticities that do not differ significantly from zero would tend to support the investment model" [23].

[9] Some of the studies reviewed by Martín et al. [37] focus on the question whether rising HCE with age is caused by aging as such or by 'proximity to death'. These studies typically analyze micro datasets from health insurance companies to compare ex post the health care costs for survivors with costs for those who have died. As our focus is on the macroeconomic level, we leave aside those studies reviewed by Martín et al. [37] which focus on the micro-level.

in time, and we take the values for the in-between years as missing.[10]

Since it is not possible to carry forward the data on the institutional dummy variables beyond 2010, we use this year as cut-off and hence choose the years 1970–2010 as the observation period. We collected data for our dependent variable 'per capita health care expenditure', which Grossman [21] uses as a measure for the demand for medical care, from the 2010/2011 vintages of the OECD Health Database. This database also contains economic, socio-demographic and even technological data (as long as they are health-related). So we also collected data on the medical price index (P^M), the compensation per employee (as a measure for w) and the share of the population above 65 years (as a measure for t) from this database. To eliminate purely monetary effects, we deflate per capita HCE as well as the compensation per employee and the medical price index with the GDP deflator. So w is defined as the real wage per employee and P^M as the relative price of medical care.[11]

Our study is the first to include the (relative) price of medical care. Grossman [21] excluded prices for medical services due to lack of data. Similarly, the other studies based on micro data excluded prices because households in the countries where the surveys were conducted (Denmark, Germany, Sweden, Switzerland) face no price tag on health thanks to the existence of comprehensive health insurance systems.[12]

However, there are problems with medical prices in the context of our study also. First, there are measurement issues: national price trends in health care must be expected to be as diverse as national schemes of price regulation, for instance (see [4]). Having said that, the data availability is not good in the first place. Only 14 out of 34 countries have reported medical price data to the OECD. In order not to shrink our sample in the cross-section dimension too much, we therefore exclude the relative medical price index from our baseline model. We include it in an alternative model, however, to test for the first time the prediction the Grossman model makes about the sign of this variable.

Grossman's measure for knowledge capital/education is the number of years of formal schooling completed. We collect annual data for the average number of years of schooling of the population aged between 25 and 64 years from Arnold et al. [2].[13] These data cover the period 1969–2004. We carry the time series forward to 2010 based on information on educational attainment of the adult population in Table A1.1a in subsequent issues of the OECD publication *Education at a Glance* [42]. This table reports the percentage of the population in different educational attainment categories, which we translate into average years of schooling applying the weighting scheme by De la Fuente and Doménech ([10]: 10, fn. 8).

The final determinant of health care expenditure predicted by the Grossman model—at least by its 'pure consumption' version—is the initial stock of financial wealth. Data on household wealth in 1970 (as percentage of nominal disposable income) are available for only three countries from the OECD (Canada, Japan and the US). However, since the initial stock does not change over time, we can use country fixed effects in our panel estimations to model the hypothesized impact of initial financial wealth on health care expenditure (see [57]). By testing the statistical significance of these country fixed effects, we can perform the test Grossman [23] suggested to discriminate between the PI and the PC sub-models.

Table 2 lists all macro-level explanatory variables for HCE that we include in the analysis. In the top-down dimension, the table has six blocks. Block 1 gives the dependent variable: the log of per capita health care expenditure at constant prices and US$ purchasing power parity.

Block 2 in the top-down dimension of Table 2 lists the so-called 'M vector variables'. In the EBA jargon, variables in the 'M vector' are included in all regressions. All the other explanatory variables, which will only be used in a sub-set of regressions, are called 'Z vector variables' (see Sect. 4 for details). The determinants of medical spending identified by the Grossman model are in the 'M vector'.

Block 3 in the top-down dimension of Table 2 lists socio-demographic factors that have been suggested as explanatory variables for HCE. In the literature, a large number of different population shares have been suggested. We choose not to include all these population shares in the EBA, however, for the following reasons. First, having too many population variables will put too large a weight on them in the EBA results. If many Z vector variables are population variables, then a large share of the regressions will consist of combinations of population variables. That is creating an imbalance. Second, different shares of the population in higher age brackets are highly correlated with the share of the population above 65 years, which we include in the 'M vector'. Including them in the 'Z vector' would generate multicollinearity

[10] As a robustness check, we treated all missing values as actually missing instead of imputing values. The results (available upon request from the authors) hardly change.

[11] Our dataset covers all 34 OECD countries except Turkey, for which no data on the compensation of employees were available, and Chile, Estonia, Israel and Slovenia, for which no employment data were available.

[12] This even implies that M more or less drops out of the individual's investment function (9) since the individual faces no direct medical costs (see [57]). This feature is circumvented when working with macroeconomic data because the society must incur the costs.

[13] See http://sites.google.com/site/bassaxsite/home/files/Solowlucasdata.zip.

problems and would thereby reduce the likelihood that any of these variables turns out to be significant. So we decided to include only one additional population variable on top of the one in the M vector: the share of the population 4 years and under, covering potentially higher than average HCE for children.

The remaining blocks in the top-down dimension of Table 2 list economic, institutional, and technological variables that have been suggested as determinants for HCE. We had to modify or drop variables vis-à-vis the literature when they were highly correlated with other explanatory variables. The main weakness of the method of extreme bounds analysis is that it cannot decently cope with strong multicollinearity.[14] Two highly correlated variables often turn individually insignificant when entered jointly and should therefore ideally not both enter the EBA.[15] We also exclude variables that would reduce the number of observations entering any regression to below 100, which leaves us with 38 explanatory variables in our unbalanced panel set-up. Table 3 provides descriptive statistics for all these variables.

Methodology: extreme bounds analysis

Extreme bounds analysis, as suggested by Leamer [33] and Levine and Renelt [35], has been widely used in the economic growth literature. The central difficulty in this research is that several different models may all seem reasonable given the data but yield different conclusions about the parameters of interest. Equations of the following general form are estimated:

$$Y = \alpha \mathrm{M} + \beta F + \gamma \mathrm{Z} + u, \tag{18}$$

where Y is the dependent variable; M is a vector of 'standard' explanatory variables; F is the variable of interest; Z is a vector of up to three possible additional explanatory variables, which the literature suggests may be related to the dependent variable; and u is an error term. The extreme bounds test for variable F states that if the lower extreme bound for β—the lowest value for β minus two standard deviations—is negative, and the upper extreme bound for β—the highest value for β plus two standard deviations—is positive, the variable F is not robustly related to Y.

As argued by Temple [56], it is rare in empirical research that we can say with certainty that one model dominates all other possibilities in all dimensions. In these circumstances, it makes sense to provide information about how sensitive the findings are to alternative modeling choices. Extreme bounds analysis (EBA) provides a relatively simple means of doing exactly this. Still, the approach has been criticized in the literature. Sala-i-Martin [47] argues that the test applied poses too rigid a threshold in most cases. Assuming that the distribution of β has at least some positive and some negative support, the estimated coefficient changes signs if enough different specifications are considered. We therefore report not just the lowest and highest coefficient estimates, but also the percentage of the regressions in which the coefficient is significantly different from zero at the 10% level. Moreover, instead of analyzing just the extreme bounds of the estimates of the coefficient of a particular variable, we follow Sala-i-Martin's [47] suggestion to analyze the entire distribution. Following this suggestion, we not only report the unweighted average parameter estimate of β, but also the unweighted cumulative distribution function [CDF(0)], that is, the fraction of the cumulative distribution function lying on one side of zero.[16]

Since our panel setup is unbalanced and contains a substantial number of missing observations, we chose not to use extensions of the EBA approach, like Bayesian averaging of classical estimates (BACE), as introduced by Sala-i-Martin et al. [48], or Bayesian model averaging (BMA).[17]

Results

Baseline model

The Grossman model posits a relationship between medical spending and the variables listed in Table 1 in levels. However, since Fisher-type panel unit root rest results (available

[14] Another limitation is the lack of treatment for endogeneity. So, as Carmignani et al. [5] point out, "in using EBA, it is more appropriate to interpret the regressors as 'predictors' instead of 'determinants'". One admittedly crude solution for the endogeneity problem used in applied consumption analysis has been to take the budget share as the dependent variable, i.e., HCE relative to GDP in the present context. In the presence of endogeneity, the error terms in HCE and GDP are likely to move in parallel so tend to cancel in the ratio. As a further robustness check, we also estimated the Grossman model specified in shares. The results (not shown, but available from the authors on request) are qualitatively not different from those for the level and growth models.

[15] The correlation coefficients of the variables used in the EBA are almost always well below 0.4, and therefore do not pose a serious problem in our set-up.

[16] Sala-i-Martin [47] proposes using the (integrated) likelihood to construct a weighted CDF(0). However, the varying number of observations in the regressions due to missing observations in some of the variables poses a problem. Sturm and de Haan [54] show that this goodness of fit measure may not be a good indicator of the probability that a model is the true model, and the weights constructed in this way are not equivariant to linear transformations in the dependent variable. Hence, changing scales result in rather different outcomes and conclusions. We thus restrict our attention to the unweighted version.

[17] Hauck and Zhang [28] use Bayesian Model Averaging to identify robust drivers of HCE growth. They work around the problem of missing observations by imputing missing values.

Table 1 Predicted partial correlations

Reduced form demand for medical care	Pure investment model (15)	Pure consumption model (17)
Wage rate (w)	+	+
Price of medical care (P^M)	−	−
Education (E)	−	−
Age (t)	+	+
Initial wealth (A_0)	0	+

Source Zweifel et al. [61], Table 3.1

upon request) suggest that some of the variables are non-stationary; correlations found between them may be spurious unless the variables are cointegrated. We carried out Westerlund ECM panel cointegration tests to see whether the log level of real per capita health care expenditure in US$ purchasing power parity (*lphce*), the log level of real wages per employee in US$ purchasing power parity (*lprwage*), the log of the population share above 65 years (*lpop65*) and the log of the average number of years of schooling of the population aged between 25 and 64 years (*lschool*) are cointegrated.[18] The test results (available upon request) mostly reject the null hypothesis of no cointegration, so spurious correlation should not be an issue. However, as a robustness check, we also specify our models in growth rates (log differences).[19]

In a first step, we regress the log level of real per capita health care expenditure (*lphce*) and its growth rate (*dlhce*) on the determinants of medical spending identified by the Grossman model (the 'M vector' variables). Table 4 shows the results. From the perspective of the Grossman model, only the real wage is statistically significant with the right (positive) sign. The relative price of medical care has always the wrong (positive) sign, but is always insignificant. The share of the population above 65 years is not significant independent of whether the relative price of medical care is included. The same is true for the schooling variable. We include country and time fixed effects in the estimations, and Hausman test results show that they are not redundant. This and the finding that the coefficients on the real wage and the relative medical price have not the same value with opposite signs favor the 'pure consumption' over the 'pure investment' version of the Grossman model.[20]

Extreme bounds analysis

For the inclusion of additional explanatory variables, we opt for Sala-i-Martin's version of extreme bounds analysis. By including up to three additional variables from the 'Z vector', we estimate in total more than 700,000 specifications. Within each of our four models (with and without the relative price of medical care and in levels or growth rates), a 'Z vector' variable is included in almost 7000 of them; the 'M vector' variables are of course always included.

Tables 5 and 6 report the results of the extreme bounds analysis for our two level models and our two growth models. Whereas Table 5 reports the results without the relative medical care price included in the M vector, Table 6 shows those where it is. The results are based on OLS estimation results that include both country and year fixed effects. The first two columns give the average of the estimated β-coefficients for that particular variable and the average standard error. The third column gives the percentage of the regressions in which the coefficient on the variable is significantly different from zero at the 10% level. The subsequent column reports the results of the cumulative distribution function (CDF): it shows the percentage of the cumulative distribution function lying on one side of zero. CDF(0) indicates the larger of these areas under the density function either above or below zero, so it will always lie between 50 and 100%. The last two columns report the lowest and highest estimated coefficients minus or plus two times their standard deviations.[21]

The first thing to note from the tables is that the inclusion of additional explanatory variables does not change the main insights from our baseline model. Among the determinants of medical spending identified by the Grossman model, only the wage emerges as a robust explanatory variable. The estimated cumulative distribution functions for the coefficients on the real wage lie to more than 90 percent on the right-hand side of zero in all four models. The underlying estimated coefficients are statistically significant in between 66% (in the level model with the relative medical price in the M vector) and 97% (in the growth model without the relative

[18] We excluded the relative price of medical care for lack of observations. Also, we had to drop eight countries when performing the panel cointegration tests because they had less than the required number of 14 observations for at least one time series.

[19] We do not convert real per capita health expenditure and the real wage into purchasing power parities (PPPs) for the growth models because when comparing growth rates, data based on constant national prices is to be preferred. PPPs should be used when levels are the object of analysis across countries (see [1]). So *dlhce* and *dlrwage* stand for the log difference of real per capita health expenditure and the real wage per employee, respectively, in constant national prices.

[20] Column 2 of Table 4 shows that the hypothesis that the coefficients on the real wage and the relative medical price have the same value with opposite signs is rejected only at the 10 percent level. In all other specifications reported in Tables 4, 7 and 8 though, this hypothesis is always very clearly rejected.

[21] Tables 9 and 10 in the appendix report EBA results for the covariates. The variables in these tables are ordered based on their estimated CDF(0) results in the levels model. Because of concerns over reverse causality, we have lagged the government share (*gsh*)—as well as per-capita real insurance premiums (*lins*).

Table 2 Macro-level explanatory variables for HCE

Measure	Definition	Suggested by	Data source	Predicted sign	Estimated sign
Dependent variable					
LPHCE	Log of per capita expenditure on health at constant prices and US$ purchasing power parity		OECD Health Data, 2011 vintage		
M vector variables					
LPRWAGE	Log of compensation per employee at constant prices and US$ purchasing power parity	Grossman [21]	OECD Health Data, 2010 vintage	+	+
LPOP65	Log of share of population 65 years and over (%)	Grossman [21]	OECD Health Data, 2011 vintage	+	±
LSCHOOL	Log of years of formal schooling completed in the adult population	Grossman [21]	Arnold et al. [2]	−	+
LRPMC	Log of relative price of medical care	Grossman [21]	OECD Health Data, 2011 vintage	−	+
Socio-demographic factors					
LACCIDENT	Log of land traffic accidents, deaths per 100,000 population	Koenig et al. [31]	OECD Health Data, 2011 vintage	+	+
LALCC	Log of alcohol intake, liters per capita 15+	Gerdtham et al. [19]	OECD Health Data, 2011 vintage	+	±
LDP	Log of population density (Population per square kilometer)	Crivelli et al. [7]	OECD Health Data, 2011 vintage, CIA World Factbook	+	+
FPR	Female participation ratio, % of active population	Gerdtham et al. [19]	OECD Health Data, 2010 vintage	+	+
LLE65	Log of life expectancy at age 65 (average for men and women)	Christiansen et al. [6]	OECD Health Data, 2011 vintage	+	+
LMORT	Log of mortality rate (Potential years of life lost per 100,000 population 0–69)	Crivelli et al. [7]	OECD Health Data, 2011 vintage	−	+
LPOP04	Log of share of population 4 years and under (%)	Gerdtham et al. [19]	EUROSTAT	+	−
LTOBC	Log of tobacco consumption, grams per capita 15+	Gerdtham et al. [19]	OECD Health Data, 2011 vintage	+	−
Economic factors					
LPGDPPC	Log of per capita Gross Domestic Product at constant prices and US$ purchasing power parity	Newhouse [40]	OECD Health Data, 2011 vintage	+	+
GSH1	Public expenditure as percentage of GDP, lagged 1 year	Hitiris [29]	OECD Health Data, 2010 vintage	+	−
PO	Dummy variable, one for countries with below-average per-capita GDP	Crivelli et al. [7]	Built based on data for per capita GDP in US$ PPP	−	−
UNEMP	Unemployment rate (% ratio to labor force)	Christiansen et al. [6]	OECD Health Data, 2010 vintage	±	−
Institutional factors					
CAPITA	Dummy variable, one for countries with capitation as the dominant means of remuneration in primary care, zero otherwise	Gerdtham et al. [19], Christiansen et al. [6]	Gerdtham et al. [19], Christiansen et al. [6], Paris et al. [44]	−	−
CASEHO	Dummy variable, one for countries with case-based remuneration in in-patient care, zero otherwise	Christiansen et al. [6]	Christiansen et al. [6], Paris et al. [44]	−	−
COPAYDUM	Dummy variable, one for countries with some copayment for either general practitioner visits or hospital stays, zero otherwise	Christiansen et al. [6]	Christiansen et al. [6]	−	±
COVERO	Insurance coverage of the population (%)	Gerdtham et al. [19]	OECD Health Data, 2011 vintage	+	+
FFSA	Dummy variable, one for countries with fee-for-services as the dominant means of remuneration in primary care, zero otherwise	Gerdtham et al. [19]	Gerdtham et al. [19], Paris et al. [44]	+	+

Table 2 (continued)

Measure	Definition	Suggested by	Data source	Predicted sign	Estimated sign
FREE	Dummy variable, one for countries with free choice of either hospital, or general practitioner or specialist, zero otherwise	Christiansen et al. [6]	Christiansen et al. [6], Paris et al. [44]	+	±
GATEKEEP	Dummy variable, one for countries with physicians as (compulsory) gatekeepers, zero otherwise	Gerdtham et al. [19], Christiansen et al. [6]	Gerdtham et al. [19], Christiansen et al. [6], Paris et al. [44]	−	±
GLOBALHO	Dummy variable, one for countries which remunerate their hospitals mainly by global budget, zero otherwise	Christiansen et al. [6]	Christiansen et al. [6], Paris et al. [44]	−	+
HCSYSPI	Dummy variable, one for countries with public integrated systems, zero otherwise	Gerdtham et al. [19], Christiansen et al. [6]	Gerdtham et al. [19], Christiansen et al. [6]	−	+
HCSYSPC	Dummy variable, one for countries with public contract (reimbursement) system, zero otherwise	Gerdtham et al. [19], Christiansen et al. [6]	Gerdtham et al. [19], Christiansen et al. [6]	+	−
LPINS1	Log of per capita insurance premiums at constant prices and US$ purchasing power parity, lagged 1 year	Karatzas [30]	OECD Health Data, 2011 vintage	+	−
MIXEDGP	Dummy variable, one for countries with a mix of capitation and fee-for-services as the dominant means of remuneration in primary care, zero otherwise	Christiansen et al. [6]	Christiansen et al. [6], Paris et al. [44]	±	−
PUHES	Public health expenditure as a share of total health expenditure	Christiansen et al. [6]	OECD Health Data, 2010 vintage	+	+
LPTA	Log of per capita expenditure on health administration at constant prices and US$ purchasing power parity	Karatzas [30]	OECD Health Data, 2010 vintage	+	+
TEXMC	The share of inpatient expenditure in total health expenditure (%)	Gerdtham et al. [19]	OECD Health Data, 2010 vintage	+	−
WS	Dummy variable, one for countries with wage and salary as the dominant means of remuneration in primary care, zero otherwise	Gerdtham et al. [19], Christiansen et al. [6]	Gerdtham et al. [19], Christiansen et al. [6], Paris et al. [44]	−	±
Technological and capacity factors					
LBEDSH	Log of acute care beds per general hospital	Giannoni and Hitiris [20]	OECD Health Data, 2011 vintage	−	+
LBEDSI	Log of acute care beds per 1000 inhabitants	Christiansen et al. [6]	OECD Health Data, 2011 vintage	+	+
LPGERD	Log of gross expenditure on R&D at constant prices and US$ purchasing power parity	Okunade and Murthy [43]	OECD Main Science and Technology Indicators	+	±
LDOCTCA	Log of the stock of practicing physicians per 1000 population	Gerdtham et al. [19]	OECD Health Data, 2011 vintage	±	−
LPHRD	Log of total expenditure on health R&D at constant prices and US$ purchasing power parity	Okunade and Murthy [43]	OECD Health Data, 2010 vintage	+	−
LREND	Log of patients undergoing renal dialysis, rate per 100,000 population	Gerdtham et al. [19]	OECD Health Data, 2011 vintage	+	−

See Tables 6 and 10 for the entries in the column 'Estimated sign'

Table 3 Descriptive statistics

	Level (log) models						Growth (dlog) models				
	Obs	Mean	Std Dev.	Min	Max		Obs	Mean	Std Dev.	Min	Max
Dependent variable											
lphce	749	7.03	0.84	4.55	8.75	dlhce	720	3.77	4.15	− 13.02	26.32
M vector variables											
lprwage	749	2.86	0.60	1.07	3.97	dlrwage	720	1.61	2.64	− 18.63	14.77
lpop65	749	2.58	0.22	1.59	3.07	dlpop65	720	1.09	1.11	− 3.17	4.94
lschool	749	2.36	0.17	1.74	2.61	dlschool	720	0.77	1.21	− 4.66	15.36
lrpmc	333	4.52	0.16	3.88	5.06	dlrpmc	319	0.65	4.12	− 51.19	17.69
Socio-demographic factors											
laccident	726	2.59	0.45	1.48	3.65	dlaccident	692	− 3.26	9.37	− 99.49	77.18
lalcc	737	2.31	0.28	1.53	2.97	dlalcc	707	− 0.04	4.03	− 22.58	23.92
ldp	749	4.05	1.52	0.53	6.21	dldp	720	0.61	0.53	− 0.74	3.80
fpr	730	41.21	5.08	24.00	48.00	dfpr	687	0.29	0.60	− 1.00	6.00
lle65	715	2.82	0.09	2.55	3.05	dlle65	679	0.83	1.16	− 4.85	7.87
lmort	726	8.49	0.30	7.76	9.31	dlmort	692	− 2.47	2.76	− 20.64	13.12
lpop04	551	1.82	0.18	1.45	2.37	dlpop04	529	− 1.05	1.99	− 8.38	4.43
ltobc	576	7.67	0.33	6.86	8.25	dltobc	549	− 1.81	5.34	− 22.78	34.93
Economic factors											
lpgdppc	749	9.63	0.66	7.74	11.35	dlgdppc	720	2.23	2.14	− 8.25	9.88
gshl	542	45.19	8.39	19.03	71.68	dgshl	513	− 0.03	1.78	− 7.01	8.92
po	749	0.54	0.50	0.00	1.00	po	720	0.53	0.50	0.00	1.00
unemp	749	6.54	4.13	0.00	23.90	dunemp	720	0.04	1.02	− 4.20	5.00
Institutional factors											
capita	702	0.16	0.37	0.00	1.00	capita	676	0.16	0.36	0.00	1.00
caseho	383	0.11	0.31	0.00	1.00	caseho	374	0.10	0.31	0.00	1.00
copaydum	749	0.23	0.44	0.00	1.50	copaydum	720	0.23	0.44	0.00	1.50
covero	682	98.01	6.52	46.50	100.00	dcovero	645	0.22	1.74	− 4.50	34.00
ffsa	688	0.46	0.50	0.00	1.00	ffsa	661	0.46	0.50	0.00	1.00
free	749	0.48	0.50	0.00	1.00	free	720	0.49	0.50	0.00	1.00
gatekeep	706	0.64	0.48	0.00	1.00	gatekeep	680	0.64	0.48	0.00	1.00
globalho	379	0.35	0.48	0.00	1.00	globalho	370	0.36	0.48	0.00	1.00
hcsyspi	749	0.34	0.47	0.00	1.00	hcsyspi	720	0.34	0.47	0.00	1.00
hcsyspc	749	0.32	0.47	0.00	1.00	hcsyspc	720	0.31	0.46	0.00	1.00
lpinsl	401	− 1.63	1.86	− 6.45	1.45	dlinsl	374	4.11	10.09	− 79.57	66.09
mixedgp	666	0.24	0.43	0.00	1.00	mixedgp	640	0.25	0.43	0.00	1.00
puhes	710	73.38	12.22	36.20	98.30	dpuhes	681	0.04	2.05	− 14.50	15.10
lpta	424	3.76	1.08	1.29	6.09	dlta	396	5.54	21.70	− 45.20	248.49
texmc	553	41.85	11.06	15.50	76.30	dtexmc	521	− 0.35	2.44	− 22.00	9.70
ws	710	0.12	0.32	0.00	1.00	ws	684	0.12	0.32	0.00	1.00
Technological and capacity factors											
lbedsh	296	5.40	0.39	4.52	6.22	dlbedsi	417	− 1.93	3.43	− 42.08	10.68
lbedsi	452	1.39	0.34	0.49	2.51	dlbedsh	270	0.20	4.69	− 30.11	27.93
lpgerd	490	8.93	1.62	5.62	12.76	dlgerd	439	4.95	4.87	− 6.15	28.04
ldoctca	370	0.86	0.33	− 0.06	1.51	dldoctca	332	2.17	3.55	− 28.79	15.40
lphrd	235	6.38	2.17	0.09	10.57	dlhrd	209	6.11	14.40	− 69.31	88.50
lrend	453	3.47	0.68	0.99	5.37	dlrend	415	6.05	8.69	− 34.92	88.85

See Table 2 for the variable descriptions. Note that for the growth (dlog) models, variables are never converted into PPPs (see footnote 19). This is indicated by the absence of the letter 'p' behind 'dl' in the variable names in the right panel of Table 3. So, for instance, 'lpgdppc' in the left panel stands for the log of per capita Gross Domestic Product at constant prices and US$ purchasing power parity while 'dlgdppc stands for the growth rate (dlog) of per capita Gross Domestic Product at constant national prices

Table 4 Baseline regressions

	(1) lphce	(2) lphce		(3) dlhce	(4) dlhce
lprwage	0.644***	0.444**	dlrwage	0.585***	0.702***
	(5.437)	(2.256)		(6.900)	(6.397)
lpop65	0.0808	− 0.0782	dlpop65	0.173	0.258
	(0.375)	(− 0.191)		(0.929)	(0.617)
lschool	0.106	0.139	dlschool	0.118	0.0913
	(0.237)	(0.271)		(1.156)	(1.516)
lrpmc		0.207	dlrpmc		0.0373
		(0.812)			(0.543)
Observations	749	333	Observations	720	319
R-squared	0.982	0.987	R-squared	0.293	0.381
Number of countries	29	14	Number of countries	29	14
Hausman test (p value)	0.000	0.000	Hausman test (p value)	0.000	0.000
rwage = − rpm (p value)		0.078	rwage = − rpm (p value)		0.000

For variable definitions, see Table 2. Two-way fixed effects were used. t statistics (clustered at the country level) in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 5 EBA results for the model without the relative price of medical care in the M vector

	Model in levels						Model in growth rates (change in logs)					
	øb	∅ se	%sign.	CDF (0)	Min. b	Max. b	øb	∅ se	%sign.	CDF (0)	Min. b	Max. b
lprwage	0.61	0.20	83.73	*96.57*	− 0.97	2.26	0.60	0.15	*97.19*	*99.34*	− 2.28	3.00
lpop65	0.00	0.27	11.46	73.47	− 2.61	2.17	0.03	0.29	4.11	74.18	− 3.52	7.90
lschool	0.19	0.42	16.11	74.46	− 2.55	6.01	0.07	0.15	3.95	74.49	− 2.12	4.27

For variable definitions, see Table 2. Two-way fixed effects were used. Each cell contains information on the estimated β-coefficients. The columns "∅ b", "∅ se", "Min. b" and "Max. b" report the average estimate, the average standard error, the minimum and the maximum of the β-coefficients plus or minus two times their standard deviations, respectively. The column "%sign." reports the percentage of cases in which the estimated coefficient estimate is significant at the 10% level. The column "CDF(0)" reports the percentage of the cumulative distribution function lying on one side of zero. The level-results are based upon a total of 189,607 regressions. The growth-results are based upon 196,758 regressions. Values above 90% are in italics

medical price in the M vector) of the regressions. The coefficient consistently averages around 0.6. The other M vector variables on the other hand are never robust if we apply Sala-i-Martin's [47] criterion: CDF(0) > 90%. Moreover, the schooling and the relative medical price variables have in each table on average the wrong (positive) sign. Even the age variable has the wrong (negative) sign on average in one table (see Table 6).

According to Tables 9 and 10 in the Appendix, not many other variables (that can be thought of as acting on the depreciation rate of human capital) can be counted as robust. Again according to the CDF(0) > 90% criterion, real per capita GDP is robust (with a positive sign) in three out of four models. This finding confirms the long-standing insight originating from Newhouse [40] that GDP drives health care expenditure.[22] The female participation rate (*fpr*)—proxying substitution from home to institutional care—is also robust (with a positive sign) in three out of four models. Real per capita expenditure on health administration (*ta*) is robust (with a positive sign) in both the level and the growth model when the relative medical price is excluded from the M vector,[23] and the unemployment rate (*unemp*) is robust (with a negative sign) in the two level models. These variables will be included in the preferred model presented below.[24] Ten

[22] Docteur and Oxley [12] call GDP "the main driving force in all studies".

[23] This variable has been suggested as a driver of total health care expenditure by Karatzas [30]. We include it as a control variable in our preferred models, although this component of HCE is of course beyond the individual's control.

[24] The dummy variable for countries with fee-for-services as the dominant means of remuneration in primary care (*ffsa*), which is robust in the two growth models, was included in the preferred growth model, but it dropped out because it contains only zeroes for the sample determined by the other variables.

Table 6 EBA results for the model with the relative price of medical care in the M vector

	Model in levels						Model in growth rates (change in logs)					
	øb	∅ se	%sign.	CDF (0)	Min. b	Max. b	øb	∅ se	%sign.	CDF (0)	Min. b	Max. b
lprwage	0.59	0.25	66.28	*92.44*	− 1.43	2.88	0.58	0.23	80.93	*95.30*	− 2.97	6.06
lpop65	− 0.03	0.37	29.30	81.75	− 3.04	3.57	0.27	0.52	7.83	74.02	− 7.23	12.40
lschool	0.39	0.53	38.00	83.06	− 4.51	6.66	0.11	0.29	17.37	77.65	− 3.02	7.59
lrpmc	0.17	0.20	33.58	82.19	− 1.35	1.69	0.38	0.16	50.83	87.24	− 0.73	3.99

For variable definitions, see Table 2. Two-way fixed effects were used. Each cell contains information on the estimated β-coefficients. The columns "∅ b", "∅ se", "Min. b" and "Max. b" report the average estimate, the average standard error, the minimum and the maximum of the β-coefficients plus or minus two times their standard deviations, respectively. The column "%sign." reports the percentage of cases in which the estimated coefficient estimate is significant at the 10% level. The column "CDF(0)" reports the percentage of the cumulative distribution function lying on one side of zero. The level-results are based upon a total of 152,665 regressions. The growth-results are based upon 162,248 regressions. Values above 90% are in italics

other variables are robust in only one of the four models, and their signs are sometimes counter-intuitive (e.g., the negative sign on the renal dialysis variable *lrend* in Table 10). These variables will hence not be included in the preferred model.

Preferred model

As a final step in our empirical analysis, we include those variables that emerge as robust as described above in the baseline. Columns (1) and (2) of Table 7 report the results for the two level models and columns (3) and (4) for the two growth models.

The relative medical price emerges as highly significant explanatory variable in both the level and the growth specifications. This is rather surprising since this variable was neither significant in the baseline model nor robust in the EBAs. As was mentioned above, medical prices have never been included in earlier attempts to test the Grossman model, so

Table 7 Extended regression results

	(1) lphce	(2) lphce		(3) dlhce	(4) dlhce
lprwage	0.653***	0.807***	dlrwage	0.541***	0.405*
	(3.400)	(3.432)		(3.852)	(2.120)
lpop65	0.151	0.252	dlpop65	− 0.177	0.0798
	(0.706)	(1.238)		(− 0.916)	(0.257)
lschool	− 0.352	− 0.496*	dlschool	0.0716	0.499*
	(− 1.253)	(− 1.866)		(0.694)	(1.804)
lrpmc		0.673***	dlrpmc		0.651***
		(4.427)			(5.562)
fpr	0.0205**	0.0350***	dfpr	0.179	0.344
	(2.069)	(5.255)		(0.584)	(0.991)
lpgdppc	0.376***	0.0718	dlgdppc	0.137	0.258**
	(2.802)	(0.279)		(1.406)	(2.265)
unemp	− 0.00927**	− 0.00793*			
	(− 2.195)	(− 1.972)			
lpta	0.0813***	0.00864	dlta	0.0434**	0.0145
	(3.928)	(0.262)		(2.313)	(0.698)
Observations	417	248	Observations	354	214
R-squared	0.992	0.997	R-squared	0.333	0.533
Number of countries	27	13	Number of countries	22	12
Hausman test (p value)	0.000	0.000	Hausman test (p value)	0.000	0.000
rwage = − rpm (p value)		0.000	rwage = − rpm (p value)		0.000

For variable definitions, see Table 2. Two-way fixed effects were used. t statistics (clustered at the country level) in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 8 Standardized extended regression results

	(1) lphce	(2) lphce		(3) dlhce	(4) dlhce
lprwage	0.464***	0.574***	dlrwage	0.343***	0.257*
	(3.400)	(3.432)		(3.852)	(2.120)
lpop65	0.0389	0.0653	dlpop65	− 0.0469	0.0212
	(0.706)	(1.238)		(− 0.916)	(0.257)
lschool	− 0.0703	− 0.0991*	dlschool	0.0208	0.145*
	(− 1.253)	(− 1.866)		(0.694)	(1.804)
lrpmc		0.126***	dlrpmc		0.649***
		(4.427)			(5.562)
fpr	0.125**	0.212***	dfpr	0.0310	0.0595
	(2.069)	(5.255)		(0.584)	(0.991)
lpgdppc	0.297***	0.0566	dlgdppc	0.0706	0.133**
	(2.802)	(0.279)		(1.406)	(2.265)
unemp	− 0.0457**	− 0.0391*			
	(− 2.195)	(− 1.972)			
lpta	0.105***	0.0112	dlta	0.240**	0.0803
	(3.928)	(0.262)		(2.313)	(0.698)
Observations	417	248	Observations	354	214
R-squared	0.992	0.997	R-squared	0.333	0.533
Number of countries	27	13	Number of countries	22	12
Hausman test (p value)	0.000	0.000	Hausman test (p value)	0.000	0.000
rwage = − rpm (p value)		0.000	rwage = − rpm (p value)		0.000

For variable definitions, see Table 2. All variables (including the dependent variable) have been standardized (mean = 0, standard deviation = 1). Two-way fixed effects were used. t statistics (clustered at the country level) in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

our paper is the first to provide empirical evidence for this explanatory variable. Since we find a significantly positive sign on the relative medical price, the Grossman model's prediction of a negative correlation between medical prices and medical spending is rejected.[25]

The exclusion of the relative medical price does not change the sign on any of the other explanatory variables in the level model, even though the statistical significance is sometimes affected. The real wage and the female participation rate are significant with a positive sign and the unemployment rate with a negative sign no matter whether the relative medical price is included, or not. The education variable on the other hand is statistically significant (at the ten percent level) only if the relative medical price is included while per capita GDP and per capita expenditure on health administration are only significant (with positive signs) if the relative medical price is excluded. Although all 'Grossman' (M vector) variables except the relative medical price have the 'correct' signs in the level specifications—the signs on the real wage and the share of the population 65 years and over are positive, and the sign on the education variable is negative as predicted by the Grossman model—the age and education variables are mostly not statistically significant.

Columns (3) and (4) of Table 7 show the results for the estimations in growth rates which we performed as a robustness check for the level models. The real wage is the only variable identified by the Grossman model as determinant of medical spending that is also statistically significant with the expected sign in the growth models. It is also economically significant.

[25] Hartwig [26] also found a significantly positive correlation between the growth rate of per capita health expenditure and the growth rate of relative medical prices.

To compare the relative impacts of the explanatory variables, we have standardized them so that all variables (including the dependent variable) have a zero mean and a standard deviation of one. Table 8 shows that a one standard deviation shock to real wage growth raises the growth rate of medical spending by around 0.3 standard deviations. In the level model, the economic impact of the real wage is even a bit stronger. The other M vector variables are either insignificant in the growth models or significant with the 'wrong' sign. Table 8 shows that the positive impact of the relative medical price on health expenditure growth is particularly strong, even stronger than the impact of real wage growth. The covariates that emerged as robust from the EBA keep their positive signs. They are not statistically significant, however, except for the growth rate of per capita expenditure on health administration in model (3) and per capita GDP growth in model (4).

Conclusion

The continuing rise in the share of health spending in GDP is a matter of considerable public concern. We believe that it is of utmost importance for public policy to understand the causes of this rise. The seminal Grossman [21, 22] model draws on household production theory to explain in a microfounded way the demand for medical care and hence medical spending. Individuals facing a depreciating human capital stock in the form of health use medical care and their own time to (re-)produce health capital. Investment in health production will be optimal when the marginal cost of health production equals the marginal benefits of the improved health status in the form of 'healthy time'. The model concludes that the real wage and aging have a positive impact on real medical spending while the impact of the relative medical price and the level of education is negative. Initial wealth has a positive influence in the 'pure consumption' version of the model, but no influence in its 'pure investment' version.

The Grossman model has been tested empirically in a set of studies over the 1980s and 1990s. Since then, attempts to test it have ebbed—maybe because the results of these earlier studies, which were based on micro data from household surveys, have been mixed and somewhat uninspiring. More recently, Zweifel [59] concluded that the Grossman model is—at least in parts—rejected by the data. This prompted us to undertake a new, and different, attempt at testing the model. First, instead of micro data from household surveys, we use a panel of macroeconomic data from the OECD. The second major difference between our approach and the earlier literature is that we check the robustness of the results by means of extreme bounds analysis (EBA). This means that, besides the determinants for medical spending suggested by the Grossman model, we include all other variables that have been suggested in the literature as determinants for health expenditure. This tests the robustness of the 'Grossman variables'.

Besides emphasizing where we depart from the earlier literature, it is also apposite to stress where do not. The most important point to mention in this context is that we test the Grossman model as it is implemented in the received literature. As pointed out by a reviewer, various opportunities for improving the model exist. For instance, the Cobb–Douglas production function used in Eq. (9), which imposes unitary elasticity of substitution (contrary to most empirical evidence), could be replaced by more flexible forms such as the translog production function. In Eq. (7), taking logs gives (in simplified notation) $\ln t^s = \ln\beta_1 - \beta_2 \ln H$, which implies the constant elasticity $\varepsilon(t^s, H) = -\beta_2$. Therefore, a 10% decrease in health stock causes an increase of $\beta_2 \cdot 10\%$ in sick time regardless of age, education, and the increase of longevity over time, which does not seem to be very credible. Likewise for Eq. (8), using $\partial \ln \delta / \partial \ln t = (\partial \ln \delta / \partial t) \times (\partial t / \partial \ln t)$, one obtains for the elasticity $\varepsilon\left(\delta, t_i\right) = -\beta_3 \cdot t_i$. If β_3 were 0.2 (a relatively low value), a person aged 40 would be confronted with a huge elasticity of − 8.0. This person would

probably not survive for much longer. Equations (15) and (17) contain parameters (e.g., β_4) that appear both in multiplicative and additive forms. In contrast to the received literature, one could run nonlinear regressions incorporating these relationships rather than modeling the 'combined' coefficients in a linear regression. Another problem seems to be that in Eq. (12), again following earlier literature, we assume the term $\psi = \delta/\left[r + \delta - \dot{\pi}/\pi\right]$ to be constant. This is problematic in a time series context. With τ denoting the year of observation, one has $\partial\psi/\partial\tau = \left\{\dot{\delta} \cdot \left[r + \delta - \dot{\pi}/\pi\right] - \delta \cdot \left[\dot{r} + \dot{\delta} - (\ddot{\pi}\pi - \pi\ddot{\pi})/\dot{\pi}^2\right]\right\} / \left[r + \delta - \dot{\pi}/\pi\right]^2$. The probability of this expression being zero is small, especially in view of the substantial increase in longevity in most OECD countries combined with a surge in the relative price of medical care. It follows that the assumption we make, which may be acceptable in a cross-section context, may not transferable to time series data. These are important theoretical issues that future scholars might want to explore.

Our aim in this paper is to inquire whether the Grossman model's predictions for what determines individual demand for medical care are also reflected in macroeconomic data. The results can be summarized as follows. The relative medical price, which our macroeconomic approach allows us to test for the first time in the empirical literature on the Grossman model, is significant with the *wrong* (positive) sign in our preferred models. It has to be stressed, however, that the quality and availability of medical price data is low. Except for the relative medical price, all other 'Grossman variables'—the real wage, age and education—have the correct sign in our models (1) and (2) in Table 7, but the age and education variables are mostly not statistically significant. The real wage is the only predictor that is robustly significant with the correct sign in all specifications, even in those where all variables are transformed into (log) differences. Hausman test results show that country and time fixed effects are not redundant. This speaks in favor of the 'pure consumption' rather than the 'pure investment' version of the Grossman model (see [23, 57]).

The bottom line of our test of the Grossman model with macroeconomic panel data is that it adds to the mixed evidence on that model that emerged from studies using micro data in the 1980s and 1990s. Except for the relative medical price, our results—especially our models (1) and (2) in Table 7—lend some support to that model against claims that it is rejected by the data. However, skeptics might still argue that our most robust finding, namely that the real wage drives real medical spending, just picks up income effects à la Newhouse [40] or 'Baumol's Cost Disease' [25]. In any case, it seems to be about time to re-open the debate on the empirical validity of the human capital model.

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Compliance with ethical standards

Conflict of interest There are no conflicts of interest or ethical issues.

Appendix

See Tables 9 and 10.

Table 9 EBA results for the covariates in the model without the relative price of medical care in the M vector

	Model in levels						Model in growth rates (change in logs)					
	øb	∅ se	%sign.	CDF (0)	Min. b	Max. b	øb	∅ se	%sign.	CDF (0)	Min. b	Max. b
lpgdppc	0.79	0.20	*95.35*	*99.13*	− 2.70	2.73	0.25	0.15	54.68	*90.82*	− 5.36	3.13
fpr	0.03	0.01	83.74	*96.52*	− 0.06	0.11	0.29	0.41	28.91	81.35	− 3.88	5.02
lbedsi	0.40	0.15	76.94	*95.46*	− 0.88	1.39	0.12	0.11	15.43	82.67	− 1.55	1.30
lpta	0.07	0.03	80.63	*95.37*	− 0.23	0.30	0.04	0.02	64.38	*91.60*	− 0.17	0.17
unemp	− 0.01	0.01	76.31	*94.44*	− 0.06	0.04	− 0.28	0.29	28.11	83.31	− 5.96	4.09
ws	0.19	0.12	66.60	*92.31*	− 6.31	5.52	− 0.46	1.18	25.66	78.83	− 42.05	49.15
gatekeep	− 0.10	0.07	61.08	*90.50*	− 2.08	5.51	− 0.29	0.81	18.47	77.78	− 22.71	21.84
lpop04	− 0.20	0.19	42.23	86.09	− 1.98	2.45	− 0.03	0.16	4.13	71.45	− 5.06	7.20
puhes	0.01	0.00	37.30	85.89	− 0.06	0.18	0.07	0.23	15.83	77.95	− 2.08	3.80
ltobc	− 0.12	0.10	33.90	85.47	− 0.66	1.03	0.04	0.03	40.48	88.07	− 0.33	0.36
gshl	0.00	0.00	46.42	85.33	− 0.03	0.02	− 0.03	0.18	1.92	66.53	− 2.21	1.37
lldp	0.99	0.57	49.21	85.22	− 8.98	7.84	0.53	0.83	28.81	84.57	− 16.42	17.09
lle65	0.91	0.76	33.37	85.15	− 5.23	5.08	0.19	0.28	6.38	78.34	− 2.34	2.45
lphrd	− 0.01	0.03	37.66	84.37	− 0.28	0.37	− 0.01	0.02	22.98	77.18	− 0.31	0.22
lrpmc	0.22	0.22	38.53	83.70	− 1.35	1.92	0.38	0.16	51.05	87.29	− 0.93	3.99
globalho	0.07	0.07	31.90	83.50	− 0.64	0.54	1.08	1.13	20.40	82.09	− 14.05	13.38
lalcc	− 0.08	0.14	30.03	82.21	− 0.92	1.18	0.08	0.09	15.78	78.28	− 0.45	1.14
texmc	0.00	0.00	23.59	81.91	− 0.04	0.03	− 0.22	0.13	58.51	89.75	− 9.95	1.97
lbedsh	0.08	0.09	24.16	81.56	− 0.70	1.16	0.00	0.09	7.23	72.42	− 0.94	0.93
capita	0.00	0.08	36.63	81.42	− 4.29	3.03	− 0.74	0.84	57.76	*90.32*	− 21.95	35.91
lrend	0.03	0.07	21.75	81.41	− 1.07	1.22	− 0.01	0.03	7.91	76.66	− 0.87	2.58
copaydum	0.03	0.03	23.62	81.41	− 0.20	0.66	− 1.34	0.83	44.20	*91.42*	− 26.39	41.37
covero	0.00	0.00	23.96	81.27	− 0.33	0.68	0.09	0.27	13.31	77.80	− 20.73	130.86
lpinsl	0.00	0.05	27.64	80.98	− 0.60	0.66	− 0.01	0.02	4.01	73.66	− 0.52	0.22
doctca	0.11	0.19	15.55	80.39	− 1.47	1.75	0.05	0.07	19.27	81.02	− 2.60	2.00
laccident	0.04	0.08	24.51	80.18	− 0.51	0.67	0.00	0.02	8.15	73.76	− 0.27	0.47
mort	− 0.09	0.28	17.46	79.90	− 1.75	2.22	0.07	0.10	11.73	77.74	-0.93	0.88
lpgerd	0.03	0.09	19.57	79.47	− 0.73	0.61	0.01	0.07	6.02	69.34	− 0.80	1.19
hesyspc	− 0.03	0.05	22.92	78.28	− 1.99	1.45	− 0.14	1.13	5.11	69.45	− 31.68	12.25
free	− 0.03	0.06	15.32	77.42	− 0.55	0.53	0.18	0.89	6.83	72.70	− 6.15	31.26
hesyspi	− 0.01	0.04	14.19	77.23	− 2.25	1.48	0.02	0.91	8.23	72.64	− 13.54	31.26
mixedgp	− 0.03	0.07	23.87	77.04	− 3.16	4.43	0.48	0.72	18.27	78.26	− 13.69	22.11
po	− 0.01	0.03	15.61	75.79	− 1.61	0.96	0.13	1.25	4.21	70.20	− 10.26	24.42
caseho	0.00	0.07	13.78	74.77	− 0.41	0.59	− 0.60	1.17	17.20	78.55	− 8.81	11.39
ffsa	− 0.01	0.09	6.65	69.07	− 0.56	0.71	1.51	0.65	78.511	*96.40*	− 2.97	7.88

For variable definitions, see Table 2. Two-way fixed effects were used. Each cell contains information on the estimated β-coefficients. The columns "∅ b", "∅ se", "Min. b" and "Max. b" report the average estimate, the average standard error, the minimum and the maximum of the β-coefficients plus or minus two times their standard deviations, respectively. The column "%sign." reports the percentage of cases in which the estimated coefficient estimate is significant at the 10% level. The column "CDF(0)" reports the percentage of the cumulative distribution function lying on one side of zero. The level-results are based upon a total of 189,607 regressions. The growth-results are based upon 196,758 regressions. Values above 90% are in italics

Table 10 EBA results for the covariates in the model with the relative price of medical care in the M vector

	Model in levels						Model in growth rates (change in logs)					
	øb	∅ se	%sign.	CDF (0)	Min. b	Max. b	øb	∅ se	%sign.	CDF (0)	Min. b	Max. b
fpr	0.03	0.01	89.45	*97.74*	− 0.14	0.09	0.64	0.42	59.15	*90.67*	− 7.96	6.71
puhes	0.01	0.00	88.78	*97.03*	− 0.09	0.25	0.38	0.24	54.73	89.40	− 8.70	15.32
ldp	1.65	0.55	83.23	*96.17*	− 13.27	15.51	1.10	1.27	34.81	84.42	55.91	39.91
lpgdppc	0.45	0.19	77.98	*95.27*	− 3.42	2.08	0.21	0.17	58.35	89.97	− 6.77	8.47
unemp	− 0.01	0.00	67.53	*92.67*	− 0.09	0.16	− 0.42	0.31	55.02	89.58	20.84	6.42
lpinsl	− 0.09	0.05	60.46	*90.83*	− 2.44	1.31	− 0.02	0.02	15.07	83.00	− 0.78	0.36
globalho	0.06	0.04	45.24	89.00	− 0.29	0.42	3.17	1.62	67.41	*93.60*	23.90	42.13
copaydum	0.04	0.03	43.88	87.01	− 0.77	0.85	− 0.89	1.22	17.98	79.64	35.82	73.32
lle65	0.88	0.61	45.49	86.96	− 2.67	4.44	0.22	0.27	20.60	84.08	− 3.32	2.84
ws	0.19	0.16	49.43	86.86	− 4.33	6.55	− 1.49	1.63	37.21	83.52	50.74	57.70
covero	0.01	0.02	41.74	86.85	− 1.33	2.51	0.60	0.97	46.79	88.23	84.78	151.20
hcsyspc	− 0.06	0.06	38.54	86.43	− 3.47	1.77	− 2.15	1.80	25.76	75.14	61.67	30.28
lbedsi	0.24	0.17	38.35	86.40	− 32.30	29.85	0.00	0.10	11.33	80.55	− 2.76	3.07
gshl	0.00	0.00	45.71	86.23	− 0.04	0.03	− 0.12	0.24	13.63	75.50	− 5.73	6.39
lbedsh	0.08	0.10	40.05	86.08	− 1.24	1.17	0.09	0.11	26.86	81.38	− 2.74	2.09
mixedgp	− 0.03	0.09	42.55	85.74	− 3.09	5.65	− 0.65	0.93	18.84	77.04	23.29	11.18
free	− 0.01	0.05	32.42	84.50	− 0.47	0.65	0.62	1.24	12.09	75.67	29.60	41.12
texmc	0.00	0.00	33.70	83.93	− 0.05	0.04	− 0.13	0.12	49.14	87.95	16.12	16.73
ltobc	− 0.03	0.09	36.85	83.40	− 1.16	1.32	− 0.02	0.03	9.46	76.12	− 0.44	0.40
gatekeep	0.04	0.09	33.50	83.37	− 3.91	4.88	− 0.52	0.90	36.52	83.53	45.00	16.67
laccident	0.02	0.09	29.37	83.18	− 0.67	0.77	0.01	0.03	11.65	74.11	− 0.43	0.93
lalcc	− 0.07	0.14	36.68	82.85	− 1.67	1.48	0.05	0.09	8.03	72.98	− 0.99	1.74
lpta	0.02	0.03	30.42	82.78	− 0.21	0.34	0.01	0.02	26.19	80.70	− 0.16	0.32
pop04	− 0.02	0.18	35.61	82.74	− 19.76	30.61	− 0.03	0.27	7.35	72.12	12.22	9.07
caseho	− 0.05	0.05	29.85	82.32	− 0.44	0.29	− 0.28	1.22	9.89	72.49	− 9.72	22.73
lpgerd	− 0.04	0.09	33.21	81.92	− 2.03	2.69	0.08	0.07	43.68	84.26	− 1.10	1.53
capita	− 0.05	0.09	31.79	81.76	− 5.82	3.45	− 0.41	1.60	53.81	88.95	74.80	59.49
lmort	0.10	0.24	25.25	79.79	− 1.58	1.70	0.13	0.14	12.88	79.97	− 1.70	1.35
ldoctca	− 0.13	0.15	25.05	79.73	− 7.97	9.47	− 0.03	0.13	9.53	71.29	− 3.51	3.38
hesyspi	0.01	0.05	20.03	79.04	− 3.19	1.74	2.10	1.49	26.86	84.78	31.05	41.12
po	− 0.01	0.03	18.17	78.75	− 4.13	0.80	− 1.23	1.08	34.32	84.76	15.15	30.62
ffsa	0.08	0.11	27.04	78.62	− 0.72	0.81	1.98	1.27	55.61	*90.03*	− 4.01	10.20
lrend	− 0.04	0.08	16.91	78.25	− 4.54	3.78	− 0.06	0.06	48.57	*90.24*	− 4.49	6.04
lphrd	0.00	0.03	20.18	78.23	− 0.68	0.66	− 0.02	0.03	29.45	83.18	− 0.54	0.32

For variable definitions, see Table 2. Two-way fixed effects were used. Each cell contains information on the estimated β-coefficients. The columns "∅ b", "∅ se", "Min. b" and "Max. b" report the average estimate, the average standard error, the minimum and the maximum of the β-coefficients plus or minus two times their standard deviations, respectively. The column "%sign." reports the percentage of cases in which the estimated coefficient estimate is significant at the 10% level. The column "CDF(0)" reports the percentage of the cumulative distribution function lying on one side of zero. The level-results are based upon a total of 152,665 regressions. The growth-results are based upon 162,248 regressions. Values above 90% are in italics

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