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Original Papers

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The income elasticity of health care spending

A comparison of parametric and nonparametric approaches

Abstract

Parametric and nonparametric estimation techniques are compared in estimating the relationship between income and health expenditures with implications for the reliability of past estimates of health expenditure income elasticity. Relative to a more flexible nonparametric approach, a parametric approach can generate over or underestimates in health expenditure. Three time series cross-section data sets are used: (a) United States state level data from 1980–1997, (b) Canadian province level data from 1965–2000, and (c) national level data for 16 OECD countries from 1960–1997. Relative to ordinary least squares, locally weighted scatterplot smoothing allows for variability in the income elasticity of health spending as income varies. Generally, results of the latter suggest that income elasticities are higher at low-income levels and lower at higher income levels. As well, these results confirm that income elasticity does vary by level of analysis with international income elasticities being generally larger than national or regional studies.

Keywords

Health expenditures · Income elasticity · Nonparametric

There is an extensive literature on the determinants of health care expenditures and, more explicitly, the income elasticity of health care expenditures. The debate over the income elasticity of health care spending has used national and international data and has focused on whether the elasticity is greater than or less than 1. The income elasticity of health expenditure can be defined as the percentage change in health expenditures in response to a given percentage change in income. Income elasticity below 1 denotes health care expenditure as an income inelastic and therefore a "necessary" good. On the other hand, elasticity estimates greater than 1 denote health care as income elastic and therefore a "luxury" good. Of course, all this means is that if the elasticity is greater than 1, health expenditures increase faster than income, while if less than 1, health expenditures increase more slowly than income.

The income elasticity of health expenditures is important for several reasons. First, income is one of the key determinants of health expenditures and understanding the determinants of health expenditures is important because of the light shed on the ultimate question: what is the optimal amount of health spending for a society? While health economists and policy analysts have determined which countries spend the most and the least of their gross domestic product (GDP) on health care, economic theory has yet to determine what the optimal percentage ought to be (see [23]). Second, the result has policy overtones for the conduct and financing of health care as those who feel that health care is a "necessity" are often on the side of greater public involvement in health care. On the other hand, many of those who feel it is a luxury would argue it is a commodity much as any other and best left to market forces alone. (For an overview of issues in public vs. private health care, see [8, 13]).

This contribution overviews the empirical literature on the determinants of health care spending and then constructs estimates using a simple nonparametric regression technique. While the relationship between health expenditure and income is well established, and the subject of much empirical investigation, the use of parametric techniques in estimation may have affected the estimates as well as subsequent estimates of income elasticity. Estimates of the income elasticity of health spending often imply that elasticity is approximately linear and constant over some range, but there is no reason why this need be so. This study finds that previous estimates of health care elasticity may be inappropriate because of the use

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of parametric techniques that assume a functional form, usually a linear one. The use of more flexible nonparametric techniques on data from the United States, Canada, and the OECD countries finds that the relationship between health spending and income is not a simple linear relationship. Elasticity varies with income level and therefore whether it is greater than or less than 1 can depend on the level of income. The results suggest that for the United States, Canada, and the OECD countries health spending is relatively income elastic at lower levels of income and more inelastic at higher levels of income.

Empirical evidence on the income elasticity of health expenditures

A literature examining the determinants of health care expenditures has developed to explain why health expenditures have risen so much in the postwar era, and what variables can be influenced to reduce costs. The studies have used international, national, and regional level data. (For an excellent survey of the international health expenditure determinants literature, see [16]). As well, these studies have used a variety of techniques and specifications. While many of the early studies have been simple bivariate regressions using cross-sections, over time the data sets have expanded to enable the use of multivariate regression on cross-sections as well as pooled time-series techniques. Most recently studies have explored issues regarding the stationarity of time series using error-correction techniques.

All of these studies have used a "determinants" approach in which per capita health care expenditures are regressed on variables believed to affect health expenditures. Included as determinants of per capita health expenditures have been income, the proportion of population aged either over 65 or under 15 years, the public share of health care spending, urbanization, amount of foreign aid, and the number of physicians per capita. Some basic results have emerged from all of these studies. First, in the long run the income elasticity of health expenditures must be approximately 1, for if it is any larger, it will take up an ever rising share of national income, whereas if it is lower, it will eventually disappear as an item. Second, for developed and most middle-income countries, income elasticities are very often close to 1 or greater than 1.

Newhouse [39, 40] regresses per capita medical expenditures on GDP per capita for 13 countries circa 1970 and finds that "over 90 percent of the variance in per capita medical expenditure in these countries can be explained by variation in per capita GDP" [39]. Newhouse finds the income elasticity for health care spending greater than 1, ranging from 1.15 to 1.31, and concludes that medical care, by the technical definition, is a luxury good. More recently Newhouse [41] has argued that while health care spending is a normal good, it is income inelastic. Over the period 1940–1990 in the United States income can only account for an increase in health expenditure of 35–70% while health spending overall has increased by over 700%. This suggests that a larger portion of the increase in health expenditures is due to other factors such as technological and demographic change. These results are consistent with an earlier study by Kleiman [29] and these studies initiated a literature viewing income as a major determinant of health expenditure that has been reinforced by subsequent studies.

Leu [31] used cross-section data for 19 OECD countries in 1974 and found income elasticities ranging from 1.18 to 1.36. Parkin et al. [43] using similar methods and data from 1980 found income elasticities of 1.12–1.18. Brown [4] used a sample of 20 OECD countries circa 1978 and estimated an income elasticity of 1.39. Gerdtham et al. [17] used a single cross-section of 19 OECD countries in 1987 and reported per capita income, urbanization, and the share of public financing to total health expenditure as positive and significant variables with the income elasticity reported at 1.33. Gbsesmete and Gerdtham [15] used a cross-sectional sample of 30 African countries in 1984 and reported that per capita GNP was the most significant factor in explaining per capita health expenditures, but the elasticity was slightly less than 1.0.

These international comparisons of health care expenditures are marked by a number of acknowledged problems. Among them are the lack of an internationally standardized definition of what constitutes health care expenditures, the difficulties in constructing exchange rate conversions for the data, and the possible correlation of input prices with the level of national income (see [31]). As a result of the latter problem the high-income elasticities estimated may reflect pricing as well as quantity or use differences across countries. A further problem with many of these studies is the small sample size. Normally the estimated elasticities have come from a small cross-section of 13–20 countries.

A remedy to the problem of small single cross-sections is the pooling of cross-sections over time. This facilitates not only international studies but also national ones with regional data. These studies have found lower estimates of income elasticity. Hitiris and Posnett [26] used 560 pooled time-series and cross-section observations from 20 OECD countries over the period 1960–1987 and found a strong and positive correlation between per capita health spending and GDP with an income elasticity of about unity. Barros [2] uses data for 24 OECD countries over the period 1960–1992 to examine differences in growth rates rather than levels and finds an income elasticity close 1. Gerdtham et al. [18] use a pooled time-series cross-section analysis for 22 countries over the period 1970–1991 and find the income elasticity of health expenditure to be in the 0.7–0.8 range. An exception to pooled time-series cross-section results with low-income elasticity is Hitiris [25] who uses data for 10 OECD countries from 1960–1991. Hitiris finds that the income elasticity of health expenditure ranges from 1.14 to 1.17. In a national-level regional study Di Matteo and Di Matteo [14] use a pooled time-series cross-section approach to estimate and examine the determinants of Canadian provincial government health spending over the period 1965–1991. The results show that the estimated income elasticity of real per capita provincial government health care expenditures is 0.77, suggesting that over this time period provincial government health expenditures were not a luxury good.

Some recent studies on the determinants of health expenditures have criticized the time series literature on the basis of the issue of stationarity and applied a cointegration approach. There are, however, alternative approaches to time-series based on the issue of stationarity. A stationary time series is 1 whose mean and variance do not change with time. If variables in a regression are nonstationary, the implication is that the regression is spurious. If the error term is stationary, the two variables are cointegrated with the error term, representing short-term deviations from that relationship. Tests for stationarity are available but their power is limited by both the quality and the time span of the data (see [10, 20, 24, 34, 37]. Hansen and King [22] use a model based on Hitiris and Posnett [26] and a complete data set from 20 OECD countries over the period 1960–1987 to show that the variables in a "standard" model of health care expenditure for 20 members of the OECD were not collectively stationary in levels. Blomqvist and Carter [3] use data from 18 OECD countries over the period 1960–1991 and also find much nonstationarity and proceed to run cointegrated models.

On the other hand, Roberts [44] uses data from 10 European community countries for the period 1960–1993 to replicate the Hitiris [25] study and finds a high degree of stationarity in the data, arguing that there is a spurious regression problem in the Hitiris model. Roberts argues that the long-run elasticity between health expenditure and income is at most 1. In a national-level study Murthy and Ukpolo [36] apply cointegration techniques to time series data from the United States over the period 1960–1987 and find that the income elasticity of health care spending is not significantly different from 1. Ariste and Carr [1] use error correction and cointegration techniques on Canadian provincial health expenditure data (1966–1998) and find an income elasticity of 0.88 and conclude that, "Les soins de santé ne représentent donc nullement un bien de luxe."

A feature of these "time series" studies is the inconclusive nature of the results in the testing. As Gerdtham and Jonsson [16] write, "The most likely explanation for the differing results is difference in methods, and it is an open question which test is most reliable." However, overall results do not differ from the main body of literature as they find that the income elasticity of health care spending is not significantly different from 1. As well, recent research suggests that stationarity may not be as serious a problem in panel data when panel level tests are employed and therefore "researchers studying national health expenditures need not be as concerned as previously thought about the presence of unit roots in the data" (see [33]).

Much attention has focused on the role of income in explaining international variations in health care expenditures. This has given rise to what Culyer [9] refers to as a "monocausal" myth, namely that health care is a luxury good because its income elasticity of demand is greater than 1. The interpretation of health care as a luxury good because of the high estimated income elasticities has been criticized because intuition often suggests that health care is more of a necessity than a luxury [9]. Moreover, since health care is heavily subsidized in many countries, one might expect that ability to pay would be a less important determinant of expenditure. Culyer [9] suggests that the luxury good view of health care may be based on a misspecification of the determinants of health with the possibility of omitted variables as a cause of the misspecification. Culyer [9] concludes that the missing variable is probably "too subtle to be readily quantified," but that it lies in the public budgeting mechanism used to fund health care.

However, the problem may also lie in the nature of the data being examined. Single cross-section cross-country studies may not be the most appropriate way to examine the determinants of health care expenditures given that the aforementioned problems can generate income elasticities greater than 1. There is the issue of changes both at a point in time and over time that suggests the necessity of pooling cross-sections as well as the use of appropriate time-series techniques. In addition, restricting analysis to one country with multiple jurisdictions that reduces the impact of price variations, institutions and labor market differences on the estimates might also prove to be a improvement. Getzen [19] indeed makes the case that income elasticity can vary with the level of analysis. Getzen has found that individual income elasticities are typically close to zero while national health expenditure income elasticities are often greater than 1. Getzen has further argued (2001, unpublished) that analysis of health expenditure requires that the units of observation should be matched to the units at which decision making for health actually occurs.

Another issue with these studies is that all of them have used parametric techniques to study the relationship between income and health expenditures. With parametric regression techniques, assumptions are made regarding the distribution of the population upon which a sample is taken (for example, a normal distribution) and specific functional forms are then assumed in estimating the relationship between variables. If data are known to follow a certain distribution, parametric techniques reduce complex problems of sample description into relatively simple parameter estimation. However, there are potential problems with the use of parametric techniques to estimate bivariate and multivariate regression relationships. First, if the true shape of the relationship is unknown, using a parametric technique can limit the possibilities for functional form and the choice of functional form can affect regression results. (For a survey of issues, see Ullah [46]). As Ullah [46] writes, estimates based on the use of a technique in which the functional form is assumed may not be "robust to any slight inconsistency between the data and the parametric specification." A second problem is that the estimates can be sensitive to the presence of outliers. A technique such as ordinary least squares (OLS) could be very sensitive to the presence of a single extreme observation and bias the results. Taken together, the potential price of a parametric technique is the possibility of "gross misspecification resulting in too high a model bias" [21].

Nonparametric estimation: an overview

An alternative that has emerged to parametric techniques is nonparametric estimation. This requires much less restrictive assumptions about the distribution of the data (for example, we may be uncertain that data are normally distributed) and as a result can "rid oneself of the need to specify in advance a particular functional form" [27]. Nonparametric methods are also sometimes referred to as "distribution-free" methods although this distinction is not entirely accurate. Some statistics used for nonparametric tests do have distributions such as the normal, *t*, or *F* distribution. As Sprent [45] writes: "the tags 'nonparametric' and 'distribution-free' apply not to the distribution of the test statistics but to the fact that the methods can be applied to samples that come from populations having any of a wide class of distributions which need only be specified in broad terms, e.g., as being continuous, symmetric, identical, differing only in median or mean, etc. They need not belong to specified families such as the normal, uniform, exponential, etc."

Nonparametric estimation attempts to deal with both the inadequacies of functional form and the inadequacies of the data with respect to outliers. For example, work by Magee et al. [32] suggests the use of age and age-squared as regressors in the context of estimating wealth-age profiles may be misleading as to the true shape of the wealth-age profile. They estimate kernel-smoothed conditional quantiles to produce quantile plots of the wealth of Canadian families given the age of the head of families. They show how nonparametric kernel-smoothed quantiles produce an upward-sloping wealth-age profile while other approaches, including using age and age-squared as regressors, produce a hump-shaped wealth-age profile. In labor economics the expression of the earnings function as a quadratic term in potential experience has been criticized as a poor approximation of the true empirical relationship between earnings and experience. Murphy and Welch [35] find the quadratic formulation understates early career earnings growth by 30–50% and overstates middle-career growth by 20–50%.

Di Matteo [11] applies nonparametric techniques to the estimation of wealth-age profiles and finds the high rates of accumulation estimated by standard studies using the quadratic age specification overestimate wealth accumulation rates. In another study Di Matteo [12] applies nonparametric techniques to the relationship between the exchange rate and international travel and finds that relative to the nonparametric technique OLS can yield substantial under- and overestimates of the dependent variable as the exchange rate varies.

Parametric and nonparametric regression approaches both involve estimating a relationship taking the general form:

$$Y_i = m(X_i) + e_i,\ i = 1 \ldots n$$

In estimating this relationship one could assume that the relationship is parametric, for example, taking on a linear form $Y_i = a + bX_i$, or one could attempt to estimate the relationship nonparametrically, that is, without reference to a specific functional form. A nonparametric regression approach involves estimating the relationship between Y and X using a smoothing procedure in which a locally weighted average is constructed around each X observation point. The amount of averaging is controlled by the weights employed in constructing the local average or what is termed the degree of smoothing. The choice of a smoothing parameter is important because there is a tradeoff between undersmoothing, which produces a closer fit to the data, and oversmoothing, which provides a better indication of the trend of the relationship.

The theory and method of nonparametric estimation techniques and data smoothing have undergone substantial development over the past 20 years, driven by the fact that pure parametric methods in curve estimation do not always meet the need for flexibility in data analysis. Also, there is the development of computer hardware that permits the use of computationally intensive techniques. The nonparametric approach provides a versatile method for exploring data relationships, provides predictions without reference to a fixed parametric model, and is useful for dealing with outliers. Pagan and Wickens [42] note that nonparametric methods can disclose features of data that are not readily apparent from the raw data and can point to more flexible parametric specification.

However, there are also limitations to the nonparametric regression approach. First, "the final decision about an estimated regression curve is partly subjective since even asymptotically optimal smoothers contain a considerable amount of noise that leaves space for subjective judgment" [21]. However, it is worth noting that while there is some arbitrariness in smoothing, smoothing is much less arbitrary than specifying an entire functional form. Second, nonparametric methods are often difficult to apply when there are many explanatory variables in a data set [32]. Pagan and Wickens [42] argue that nonparametric methods will likely never replace parametric techniques because to work as predicted by asymptotic theory, very large sample sizes are needed. In addition, since bandwidths for the smoothing process must always be selected, this can introduce an element of arbitrariness into the estimation process. Third, there is not yet a well-developed and accessible body of applied literature on the significance of nonparametrically estimated regression results.

The data

There are three basic data sets used in this paper: (a) United States state-level data for the period 1980–1997, (b) Canadian province-level data for the period 1965–2000, and (3) national level data for 16 OECD countries (including Canada and the United States) for the period 1960–1997. These data therefore cover a broad range of institutions, economic conditions, and heath care funding systems. All three data sets are time-series cross-sections and the variables are defined in Table 1.

The United States health data are state-level data for 50 states plus the District of Columbia obtained from the Health Care Finance Administration web site (www.hcfa.gov/stats/nhe-oact/). The health expenditure variable used is personal health care expenditure which in 1999 accounted for approximately 87% of United States national health expenditures – the remainder being expenditures in administration, public health, investment, research, and construction. Real per capita personal health expenditure (RPHLTC) was constructed by dividing personal health care expenditure by state population and deflating using a regional consumer price index. Estimates of state population, the population proportion over age 65 (PROP65) and gross state product were also obtained from this data source. Real per capita income (RGSPC) was obtained by dividing gross state product by population and again deflating with the appropriate regional consumer price index. The regions are New England, Mideast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountains,

Table 1
Variable definitions used in the study

United States	
RPHLTC	Real (1982–1984 dollars) per capita personal health expenditures
RGSPC	Real (1982–1984 dollars) per capita Gross State Product
PROP65	The proportion of population aged 65 and over
NEWENG	1 if New England, 0 otherwise
MIDEAST	1 if Mideast, 0 otherwise
GRLAKE	1 if Great Lakes, 0 otherwise
PLAINS	1 if Plains, 0 otherwise
STHEAST	1 if Southeast, 0 otherwise
STHWEST	1 if Southwest, 0 otherwise
ROCKIES	1 if Rocky Mountain, 0 otherwise
FARWEST	1 if Far West, 0 otherwise
Canada	
RPRGHX	Real (1986 dollars) per capita provincial government health expenditures
RGDPC	Real (1986 dollars) per capita provincial gross domestic product
PROP65	The proportion of population aged 65 and over
RFEDTRC	Real (1986 dollars) per capita federal cash transfers to province
NFLD	1 if Newfoundland, 0 otherwise
PEI	1 if Prince Edward Island, 0 otherwise
NS	1 if Nova Scotia, 0 otherwise
NB	1 if New Brunswick, 0 otherwise
QUE	1 if Quebec, 0 otherwise
ONT	1 if Ontario, 0 otherwise
MAN	1 if Manitoba, 0 otherwise
SASK	1 if Saskatchewan, 0 otherwise
ALTA	1 if Alberta, 0 otherwise
BC	1 if British Columbia, 0 otherwise
Sixteen OECD countries	
RHLTC	Real (US$-PPP adjusted) per capita total health expenditures
RGDPC	Real (US$-PPP adjusted) per capita Gross Domestic Product
PROP65	The proportion of population aged 65 and over
AUSTRAL	1 if Australia, 0 otherwise
AUSTRIA	1 if Austria, 0 otherwise
BELGIUM	1 if Belgium, 0 otherwise
CANADA	1 if Canada, 0 otherwise
FINLAND	1 if Finland, 0 otherwise
FRANCE	1 if France, 0 otherwise
ICELAND	1 if Iceland, 0 otherwise
IRELAND	1 if Ireland, 0 otherwise
ITALY	1 if Italy, 0 otherwise
JAPAN	1 if Japan, 0 otherwise
NORWAY	1 if Norway, 0 otherwise
SPAIN	1 if Spain, 0 otherwise
SWEDEN	1 if Sweden, 0 otherwise
SWITZER	1 if Switzerland, 0 otherwise
UK	1 if United Kingdom, 0 otherwise
USA	1 if United States, 0 otherwise

and Far West. The CPI data were for urban centers with 1982–1984=100 and was obtained from the Bureau of Labor Statistics web site. For each region the index used is as follows: New England, CPI Boston; Mideast, CPI New York–New Jersey; Great Lakes, CPI Chicago–Gary–Lake County; Plains, CPI Midwest Urban; Southeast, CPI Atlanta; Southwest, CPI Dallas–Fort Worth; Rocky Mountains, CPI Midwest Urban; Far West, CPI San Francisco. The states in each region are as follows:

- New England: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
- Mideast: Delaware, District of Columbia, Maryland, New Jersey, New York, Pennsylvania
- Great Lakes: Illinois, Indiana, Michigan, Ohio, Wisconsin
- Plains: Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
- Southeast: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississipi, North Carolina, South Carolina, Tennessee, Virginia, West Virginia
- Southwest: Arizona, New Mexico, Oklahoma, Texas
- Rocky Mountains: Colorado, Idaho, Montana, Utah, Wyoming
- Far West: Alaska, California, Hawaii, Nevada, Oregon, Washington

The total data set therefore consists of 51 cross-sections over 18 years for a total of 918 observations. The 51 cross-sections were grouped into eight regional groupings and dummy variables created for them (see Table 1 and above).

The Canadian data were obtained from Statistics Canada (CANSIM) and the Canadian Institute for Health Information (www.cihi.ca). In Canada the federal and provincial governments jointly finance public expenditures on health, but under the provisions of the British North America Act it is the provincial governments that deliver publicly funded health care to citizens. Provincial governments in Canada are responsible for approximately 70% of health care expenditures in Canada, and they are financed by a combination of own-source revenues and federal transfers. The Canadian data are for ten provinces over the period 1965–2000, and the health expenditure variable is defined as real per capita provincial government health expenditures (RPRGHX) and was deflated using the provincial consumer price index (1986=100). The income variable is provincial gross domestic product, and it was converted to real per capita income (RGDPC) by dividing it by provincial population and adjusting for inflation again by using the CPI (1986=100) for each province. Additional variables used in the Canadian data set are the proportion of population over age 65 years (PROP65) and real per capita federal cash transfers (RFEDTRC) to the provinces given the importance of federal transfer funding to the provincial governments. The federal cash transfer revenue variable is important to any study of the determinants of Canadian real per capita health care expenditures because transfers are an important source of revenue to Canada's provincial governments although they vary in importance across the country. Historically about 20% of provincial government revenue was obtained from federal transfers, but this declined to approximately 15% by the middle 1990s as the result of the federal government's deficit-fighting agenda and reductions in provincial transfers. In per capita terms the largest federal transfer recipients were the Atlantic provinces, Quebec, and the Prairie provinces of Saskatchewan and Manitoba. The total data set therefore consists of ten cross-sections over 36 years for a total of 360 observations. Dummy variables were again specified for each province (see Table 1).

The international data are from 16 OECD countries. The countries were selected in terms of completeness for all the key variables for the maximum time period possible. They are: Australia, Austria, Belgium, Canada, Finland, France, Iceland, Ireland, Italy, Japan, Norway, Spain, Sweden, Switzerland, United Kingdom, and United States. The data are from the period 1960–1997 and are taken from the OECD Health Data 2000 data set which contains health expenditure, economic, and demographic data. The health expenditure variable is total expenditures on health while the income variable is GDP. Both variables are converted into United States purchasing power parity (PPP) dollars figures to facilitate international comparisons. Real per capita income (RGDPC) is derived by dividing GDP in US-PPP dollars by population while real per capita total health expenditures (RHLTC) divided total expenditures on health in US-PPP dollars by population. The total data set consists of 16 cross-sections over 38 years for a total of 608 observations. Additional variables are the proportion of population over age 65 years (PROP65) as well dummy variables for the 16 nations (see Table 1).

Estimation

In this section OLS estimates are compared to estimates using the locally weighted scatterplot smoothing (LOWESS) technique developed by Cleveland [5]. Cleveland [6] actually refers to the technique as LOESS, which is short for local regression. Hardle [21] uses the term LOWESS to describe what he terms locally weighted scatterplot smoothing. The STATA Manual (release 4, volume 2, p. 486) refers to the technique as robust locally weighted regression and references Cleveland [5, 6]. LOWESS is used for a number of reasons. For example, one could use an alternative technique such as the Nadaraya-Watson estimator that uses

Table 2
OLS regression model for the United States. Dependent variable: RPHLTC

Variable	Model 1		Model 2	
	Coefficient	*t* statistic	Coefficient	*t* statistic
RGSPC	0.0571	9.817	0.0704	19.98
PROP65			13111.0	17.32
NEWENG			–1093.9	–11.63
MIDEAST			–1086.8	–10.74
GRLAKE			–1014.4	–11.42
PLAINS			–1176.1	–11.85
STHEAST			–1057.1	–12.48
STHWEST			–1061.0	–12.18
ROCKIES			–1096.6	–13.05
FARWEST			–1064.2	–12.26
Constant	729.60	7.877		
R^2 adjusted	0.4159		0.6696	
Income elasticity (at means)	0.57		0.70	

Table 3
OLS regression model for Canada. Dependent variable: RPRHGX

Variable	Model 1		Model 2	
	Coefficient	*t* statistic	Coefficient	*t* statistic
RGDPC	0.0473	17.04	0.0430	14.31
PROP65			8962.0	14.59
RFEDTRC			0.2155	10.19
NFLD			–663.34	–22.5
PEI			–1074.0	–22.40
NS			–940.57	–24.16
NB			–894.20	–25.69
QUE			–684.76	–22.07
ONT			–881.06	–20.23
MAN			–968.06	–24.01
SASK			–1017.4	–21.54
ALTA			–815.45	–18.45
BC			–881.35	–18.86
Constant	197.94	4.46		
R^2 adjusted	0.4765		0.9212	
Income elasticity (at means)	0.79		0.72	

Table 4
OLS regression model for 16 OECD countries. Dependent variable: RHLTC

Variable	Model 1		Model 2	
	Coefficient	*t* statistic	Coefficient	*t* statistic
RGDPC	0.0940	42.74	0.1018	32.67
PROP65			–4676.7	–5.143
AUSTRAL			176.20	2.965
AUSTRIA			407.56	3.839
BELGIUM			376.34	3.735
CANADA			270.00	4.739
FINLAND			267.34	3.542
FRANCE			444.41	4.696
ICELAND			174.85	2.875
IRELAND			334.80	3.627
ITALY			342.58	3.816
JAPAN			86.367	1.479
NORWAY			371.12	3.651
SPAIN			265.99	3.211
SWEDEN			572.23	4.999
SWITZER			325.20	3.818
UK			325.20	3.818
USA			629.61	5.284
Constant	–157.62	–11.07		
R^2 adjusted	0.9236		0.9520	
Income elasticity (at means)	1.22		1.32	

what is referred to as kernel estimation (see [27, 38, 47]). First, LOWESS is popular because of the intuition involved in understanding its use: one can view the technique as the application of a series of overlapping locally weighted regressions. Second, it has the desirable property of "closely following the line" and thus produces good fits [27]. Finally, and most important for applied economists, it is readily available in a number of popular statistics packages including STATA and SHAZAM.

LOWESS starts off with a local polynomial least squares fit and then makes the estimate more robust by using weights from the local neighborhood around the observation point. Given a scatterplot (X_i, Y_i), i=1,...n, the fitted value at X_k is the value of a polynomial fit to the data using weighted least squares, where the weight is large if X_i is close to X_k and small if it is not. In fitting a LOWESS curve the crucial choices to be made are the smoothing parameter and the degree of the fitted polynomial [5]. (The mathematical details of constructing LOWESS estimates are available in [5, 6, 21]).

The smoothing parameter ranges from between 0 and 1 while the degree of the polynomial can be linear or quadratic. The choice of the smoothing parameter and the degree of the polynomial are choices based on a combination of judgment and trial and error. While for LOWESS the bandwidth choice is partly a subjective procedure, the choice of bandwidths in nonparametric regression can be a more rigorous procedure when selected by cross-validation (see [21, 32]). In cross-validation the range over which the weighting is to be performed is determined by minimizing a loss function. The smoothing parameter is essentially a bandwidth over which the locally weighted regression is to be estimated with larger smoothing parameters associated with greater smoothing. For example, if the smoothing parameter is 0.2, 20% of the observations form the neighborhood around the local point to be estimated. Ideally one should try to pick a value of the smoothing parameter that is as large as possible without distorting patterns in the data. As for the degree of the polynomial, Cleveland [5] argues that the linear polynomial strikes a balance between the advantage of being computationally simpler and the need for flexibility to reproduce patterns in the data. The estimates were performed using SHAZAM 8.0 for MacIntosh. (The STATA LOWESS estimating algorithm specifies running-line least squares smoothing and the use of Cleveland's tricube weighting function.)

Increases in the bandwidth or smoothing parameter reduce variations in the curve, but as this is done, patterns and trends in the data become less pronounced. Choosing the smoothing parameter requires some judgment, but there is a procedure that can be followed which utilizes residuals [7]. Graphing the residuals against the independent variable at various degrees of LOWESS smoothing indicates whether there is some dependence of the residuals on the independent variable. The closer the graph of the residuals is to a horizontal line, the more optimal the amount of smoothing. As a rule, one should begin with small values of the smoothing parameter and keep increasing them until the residual graph just begins to show a pattern and then use a slightly smaller value for the smoothing parameter. In this study it was opted to select a maximum smoothing parameter of 0.8 to emphasize the longer-term trend in the data.

Our analysis begins by presenting parametric OLS estimates for the United States, Canada, and the OECD. It should be noted that a pooled times series cross-section technique such as that of Kmenta [30] might be more appropriate, but given that there were 51 cross-sections and only 18 years of observations for the United States, the technique failed for the data from the United States. Pool time series cross-section estimates generally provide a lower estimate of income elasticity vs. straight OLS. For the regressions for Canada and the OECD, the pooled time series technique yields income elasticities of 0.7 and 1.2 respectively.

The results are presented in Tables 2, 3, 4 for a basic parametric model with income and constant as the only variables (model 1) and a broader parametric model that adds the proportion of population over age 65 years and regional variables and in the Canadian case federal cash transfers (model 2).

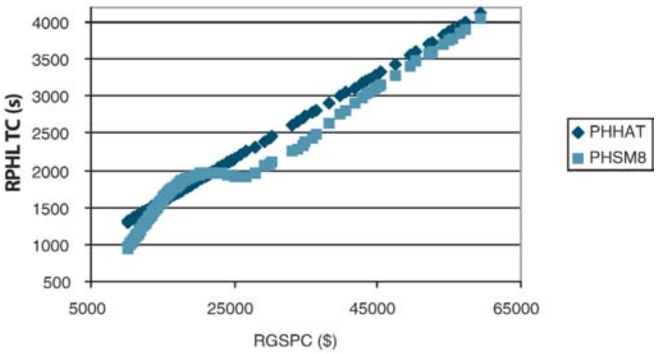

Fig. 1 ◀ **Regressions of real per capita personal health expenditure on real per capita income, United States 1980–1997. LOWESS (PHSM8) vs. OLS (PHHAT). LOWESS bandwidth=0.8**

These parametric results show that per capita health expenditures are positively related to income and the proportion of population over age 65 years (except for the OECD case) and in the Canadian case federal cash transfers. The income elasticity of health spending (evaluated at mean income) in the broader model is low for the United States and Canada, at 0.70 and 0.72, respectively, but is high for the 16 OECD countries, at 1.21. [These models were also estimated in log-log specification resulting in the income coefficient being an elasticity. The log-log results for model 1 and model 2, respectively, are as follows: United States (0.68, 0.95), Canada (1.01, 0.97), OECD (1.30, 1.28).]. This difference in income elasticity based on level of analysis provides support for Getzen's argument [19] that health care is neither a luxury or a necessity since income elasticity varies with level of analysis. The higher income elasticity for the set of OECD countries than the regional estimates is due mainly to the fact that the effect of income on health expenditures occur mainly at the level where the budget constraint is fixed. The budget constraint is almost always the binding determinant of health care expenditures at the national level. On the other hand, insurance, government provision, and family resources usually keep personal income from being as binding at an individual or often even a regional level (Getzen, unpublished, 2001).

Figures 1, 2, 3 provide the fitted values of a simple regression of per capita health expenditures on per capita income (model 1) for both OLS and LOWESS for the United States, Canada, and the 16 OECD countries. The LOWESS regression shows a nonlinear relationship that also reveals a more variable relationship between income and health expenditures. For the United States (Fig. 1) health expenditures rise more steeply for the LOWESS estimates (PHSM8) than OLS (PHHAT) at the lower levels of income, then become quite inelastic before rising once again quite quickly. The estimates were ranked by income level and elasticities calculated for each income level so that average elasticities by income range could then be presented (see Table 5). (Income elasticity at each income was defined as the percentage change in per capita health spending over the percentage change in per capita income.) For the United States OLS generates elasticities by income range that vary from just over 0.5 to just over 0.7. For LOWESS the average income elasticity for the $10,000–15,000 per capita real gross state product is over twice that for OLS. For the next range it declines, but it is still higher than for OLS. Only in the $20,000–25,000 range is the elasticity for OLS greater than that for LOWESS. For the United States LOWESS generates higher income elasticities for most of the income expenditures. These are substantial differences and imply substantial under and overestimates of spending for forecasting purposes. Moreover, the LOWESS estimates suggest that the income elasticity of health expenditures in the United States is highest for low and high income states.

For Canada's provinces (Fig. 2) the results show provincial government health expenditures rising more steeply for LOWESS (PRSM8) than OLS (PRHAT) at lower income levels and then a reversal with OLS rising more steeply than LOWESS at the higher income levels. The results also show that income elasticities for LOWESS are higher than OLS at lower income levels but higher for OLS at higher income levels. For per capita provincial GDP in the $6,000–10,000 range (Table 5) LOWESS shows provincial government health expenditures to be very income elastic. Moreover, LOWESS shows diminishing average elasticities as income rises whereas OLS shows them to be rising. The differences are again substantial. For example, for provincial per capita GDP in the $10,000–15,000 range a 1%

Table 5
Average elasticity comparisons

Income range	OLS	LOWESS
United States: OLS (PHHAT) vs. LOWESS (Phsm8) in U.S. dollars		
$10,000–15,000	0.52	1.19
$15,000–20,000	0.57	0.70
$20,000–25,000	0.67	0.31
$25,000+	0.74	0.81
CANADA: OLS (PRHAT) vs. LOWESS (PRSM8) in Canadian dollars		
$6,000–10,000	0.68	1.40
$10,000–15,000	0.76	1.15
$15,000–20,000	0.81	0.62
$20,000+	0.84	0.21
OECD: OLS (HLHAT) vs. LOWESS (HLSM8) in U.S.-PPP dollars		
$2,000–5,000	2.48	1.53
$5,000–10,000	1.31	1.22
$10,000–15,000	1.15	1.04
$15,000–20,000	1.11	0.82
$20,000+	1.08	0.71

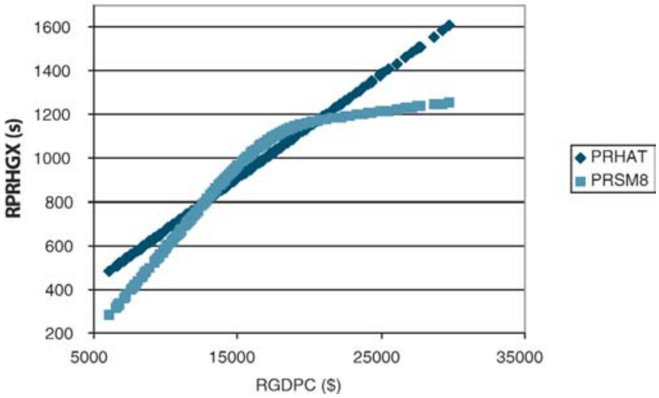

Fig. 2 ◀ **Regressions of real per capita provincial government health expenditure on real per capita income, Canada 1965–2000. LOWESS (PRSM8) vs. OLS (PRHAT). LOWESS bandwidth=0.8**

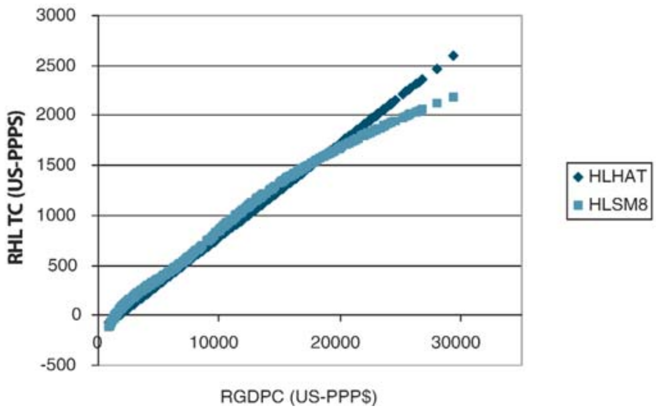

Fig. 3 ◀ **Regressions of real per capita health expenditure on real per capita income. Sixteen OECD countries. LOWESS (HLSM8) vs. OLS (HLHAT). LOWESS bandwidth=0.8**

increase in real per capita GDP would generate approximately a 1.2% increase in health spending using LOWESS and a 0.8% increase using OLS.

Finally, for the 16 OECD countries (Fig. 3) the pattern of differences between LOWESS (HLSM8) and OLS (HLHAT) again occurs although the differences are not as great as for the two previous national examples. LOWESS and OLS generate very similar estimates for low to middle-income ranges but larger divergences occur as income rises. Elasticities generated via OLS actually exceed LOWESS estimates for all income ranges but are greatest in the \$2,000–5,000 per capita GDP range. The most important difference is that LOWESS suggests that international health expenditures are income elastic at lower income ranges and income inelastic at higher income ranges. OLS on the other hand generates income elastic estimates at all the income ranges.

Conclusions

This study compared simple parametric and nonparametric estimation techniques to estimate the relationship between income and health expenditures. The results have implications for the reliability of past estimates of health expenditure income elasticity. Most studies of health expenditure determinants have relied on parametric regression models that essentially impose linear functional forms on the relationship between health spending and income. Relative to a nonparametric approach, which allows for flexibility in the relationship between income and health expenditure, a parametric approach can generate substantial over or under-estimates in health expenditure. These differences naturally extend to estimates of income elasticity.

While OLS generates estimates of income elasticity that suggest that overall health expenditures are either elastic or inelastic, LOWESS allows for variability in the income elasticity of health spending as income varies. Generally, LOWESS suggests that income elasticities are higher at low income levels and lower at high income levels. In addition, as income varies, health expenditures can go from being income elastic to income inelastic or vice versa. (A criticism of these results is that neither the OLS or the LOWESS estimates take potential time-series issues into account. On the other hand, these issues are given for both techniques and there is no reason why OLS might be more affected than LOWESS or vice versa.) As well, the results in this paper confirm that income elasticity does vary by level of analysis with international income elasticities (OECD) being generally larger than national or regional studies (United States and Canada). Therefore health expenditure elasticity depends not only on the level of analysis but also the range of income and economic development an economy finds itself at. The results in this paper suggest that as incomes rise health expenditures become more *income inelastic*. Moreover, these results are consistent over three data sets that cover a broad range of institutions, economic conditions and health care funding systems suggesting the basic strength of the relationship between health expenditure and income.

An implication for the long-term burden of health care spending is that health care need not necessarily consume a rising share of national output and as incomes rise, the health expenditure to GDP ratio will likely stabilize. The optimal value of the health expenditure to GDP ratio for any society in the long run, however, depends not only on income level but on costs, technological change, and individual preferences. In addition, that health care becomes less of a luxury as incomes rise makes intuitive sense given that as incomes rise, other needs and preferences also must be satisfied.

These results show that simple nonparametric techniques such as LOWESS should form part of the health economist's arsenal. The problem is not with parametric estimation per se as with applying a functional form without fully exploring the data. It should be noted that results obtained using LOWESS can also be obtained using more flexible parametric specifications such as splines. However, to find more complex patterns in the data, one must be looking for them, and a technique such as LOWESS can uncover complex patterns.

However, nonparametric regression techniques are not a complete substitute for parametric techniques for several reasons. First, they are computationally intensive and sometimes can be applied only to very large data sets after "binning" has been performed, and by binning data one loses some of the diversity in a data set. This has become less of a problem in recent years given improvements in computers and statistical software programs. Second, a technique such as LOWESS is not easily extended to multivariate cases. However, this limitation can be partially addressed by employing partial linear models that combine parametric and nonparametric techniques. (Nonparametric estimators can be combined with parametric specifications; see Jones [28]). Nevertheless, nonparametric techniques, when used in conjunction with parametric methods, are very useful for developing insights into more sophisticated patterns and trends in a data set.

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