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Rising health spending, new medical technology and the Baumol effect

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Abstract in English

Health expenditure as a share of GDP rises in most OECD countries. One of the possible causes is the so-called Baumol effect, which may arise if labour productivity in health care grows more slowly than in the overall economy. If in addition demand for health care is inelastic, then the share of health spending in GDP will rise over time. This paper estimates the Baumol effect in health spending, using a panel data set of OECD countries. We do indeed find that one percentage growth in economy-wide labour productivity is associated with about 0.5 percent growth in real health spending. This implies that economy-wide productivity growth leads to higher real health spending.

Key words:
Baumol effect, health spending, panel data

JEL code: H51, I11

Abstract in Dutch

Het aandeel van de zorguitgaven in het BBP stijgt in de meeste OESO-landen. Een mogelijke oorzaak is het zogenoemde Baumol-effect, dat optreedt indien de arbeidsproductiviteit in de zorg langzamer stijgt dan in de rest van de economie. Als bovendien de vraag naar zorg inelastisch is, dan neemt het aandeel van de zorguitgaven in het BBP toe. Dit paper presenteert schattingen van het Baumol-effect in de zorg op basis van paneldata van OESO-landen. We vinden dat 1 procent arbeidsproductiviteitsgroei in de economie als geheel gepaard gaat met 0,5 procent groei van de reële zorguitgaven. Dit betekent dat arbeidsproductiviteitsgroei in de economie als geheel leidt tot hogere zorguitgaven.

Steekwoorden:
Baumol-effect, zorguitgaven, paneldata

Contents

Summary

Health expenditure as a share of GDP rises in most OECD countries. One of the possible causes is the so-called Baumol effect, which may arise if labour productivity in health care grows more slowly than in the overall economy. If in addition demand for health care is inelastic, then the share of health spending in GDP will rise over time. This paper estimates the Baumol effect in health spending, using a panel data set of OECD countries. We will attempt to answer two questions:

1. How large is the Baumol effect in health care?
2. What does the estimated Baumol effect tell us about cost-reducing technological change in health care?

These questions will be answered by regressing real health spending on economy-wide productivity growth (GDP per hour worked), controlling for GDP per capita. If a Baumol effect is present in health spending, then we would expect that economy-wide productivity growth leads to higher real health spending. We do indeed find a sizeable Baumol effect: one percentage growth in economy-wide labour productivity is associated to with about 0.5 percent growth in real health spending. In addition, we find plausible values for the effect of real income growth on health spending, consistent with income elasticities for health spending reported in the literature. We infer from the estimation results that labour productivity growth in health care was 0.2 to 0.4 times as large as labour productivity growth in the economy as a whole.

1 Background

New medical technology is widely seen as a major (if not the main) driver of health spending (e.g. OECD 2006). If this view is correct, then cost-reducing new technology must have been less important than new medical technology that has resulted in the *treatment expansion*: treatment of hitherto untreated diseases or better (but more expensive) treatment of diseases that could already be treated.

The consensus view that new medical technology has on net led to higher spending is based on decompositions of past health spending; Newhouse (1992) is the classic reference. In this decomposition approach, one first determines the share of the increase in health spending that can be explained by measurable factors such as income growth. The unexplained residual is then attributed to technological change. Whether such a ‘residual approach’ leads to correct results depends critically on whether all relevant factors other than technology have been taken into account. Otherwise, the residual would be ‘polluted’ by omitted variables. Tellingly, Ambramovitz, the pioneer of residual analysis in growth economics, labelled the residual a measure of our ignorance.

Recent micro-economic evidence suggests that cost-reducing technological progress plays a significant role in health care. In particular, the work of Lichtenberg (2007) suggests that each dollar spent on new pharmaceuticals leads to 4 dollars in cost savings elsewhere in the health system. This implies that at least this type of technological progress has been expenditure reducing rather than expenditure increasing.

If technological progress has mainly resulted in treatment expansion rather than cost savings, then we would expect to find a sizeable Baumol effect in health spending: productivity growth in the rest of the economy should then lead to a higher relative price of health care and hence (given that demand for health care is price-inelastic), higher real spending on health. Conversely, if Lichtenberg’s findings are representative of health care more broadly (i.e. rapid cost-saving technological progress), then the Baumol effect in health spending must be small.

Empirically there is strong evidence for the presence of Baumol effects. For example, Nordhaus (2006) uses detailed data on economic activity by industry to analyse different Baumol-type diseases. One of the questions he poses is whether low relative productivity growth leads to high relative price increases. Using different industry combinations, Nordhaus (2006) regresses average annual logarithmic change in price on a measure of the annual logarithmic change in productivity. The hypothesis of a cost-price disease due to slow productivity growth is strongly supported - industries with relatively lower productivity growth show a percentage-point for percentage-point higher growth in relative prices.

In this paper, we focus on the Baumol effect in health spending, using a panel data set of OECD countries. We will attempt to answer two questions:

1. How large is the Baumol effect in health care?
2. What does the estimated Baumol effect tell us about the amount cost-reducing technological change in health care?

These questions will be answered by regressing real health spending on economy wide productivity growth (GDP per hour worked), controlling for GDP per capita. The estimated coefficient tells us to what extent economy-wide productivity growth leads to higher real health spending. If the Baumol effect is an important driver of higher health spending, then this coefficient should be large (close to unity). If the Baumol effect is unimportant (i.e. if cost-reducing technological progress has been substantial) in health care, then the estimated coefficient should be small (close to zero).

The paper is structured as follows. The next section presents the theoretical model. Section 3 discusses the data, while section 4 presents estimation results. Section 5 combines the estimation results with information on non-technological determinants of health spending in order to infer the rate of labour saving technological progress in health care. Section 6 concludes.

2 The Theoretical Model

In this section, we present the theoretical model, which is used as a starting point for our econometric analysis and for the inferences that will be drawn from these estimates.

Changes in nominal health spending may be decomposed into changes in prices and changes in the volume of health services consumed (Q):

$$\frac{\Delta H}{H} \equiv \frac{\Delta P_h}{P_h} + \frac{\Delta Q}{Q} + \frac{\Delta P_h}{P_h}\frac{\Delta Q}{Q} \tag{1}$$

where

H	=	nominal health spending
$\Delta H / H$	=	rate of change in nominal health spending over time
Q	=	the volume of health services consumed
$\Delta Q / Q$	=	rate of change in health volume over time
P_h	=	price of health services
$\Delta P_h / P_h$	=	nominal rate of change in price of health services *at constant quality*

In what follows, we ignore the last term in equation (1), which will be small for small changes in price and volume.

It is important to stress that *quality changes are included in Q,* so that $\Delta P_h / P_h$ captures price increases at constant quality. Thus $\Delta Q / Q$ is a hedonic index of the growth in health volume. Empirically it is very hard to make this type of price/volume split (Newhouse, 1992). As a consequence, price increases in health care are often contaminated by quality increases (Cutler en Berndt (2001)). The main reason is that it is hard to measure and value quality improvements in health care. This is the main cause of the uncertainty surrounding the effects of technological progress on health spending. One of the advantages of our approach is that we do not need to empirically make a volume/price split.

We assume that changes in health volume, *including changes in quality*, are determined by the following equation:

$$\frac{\Delta Q}{Q} = gZ + h\left(\frac{\Delta P_h}{P_h} - \frac{\Delta P}{P}\right) \tag{2}$$

where Z is a vector including the determinants of the volume of health spending other than price (e.g. an exogenous trend, growth in real income, demographic changes, etc.), g is a vector of coefficients (including the income elasticity of demand for health care) and h is the price elasticity of demand for health care ($h < 0$).

We model the change in the price of health as follows. First, at a given state of technology, economy-wide price inflation will translate one to one into health prices, still measured at constant quality. Second, according to Baumol's law, lower labour productivity growth in health care translates into an additional price increase in health. This is because economy-wide labour productivity growth translates one to one into wages (below we will present empirical evidence corroborating this statement). In order to keep and attract workers, wages in the health care sector will have to keep up with economy wide wages. As a result, the relative price of health services will go up. If we assume that the productivity of factors of production other than labour grows at the same rate in health care as in the rest of the economy, then the excess price increase in health services depends only on the labour share of health services. Denoting the labour share in health by *b*, we have:

$$\frac{\Delta P_h}{P_h} = \frac{\Delta P}{P} + b\left(\frac{\Delta A}{A} - \frac{\Delta A_h}{A_h}\right) \tag{3}$$

where

$\Delta P / P$	=	economy-wide rate of inflation (captured by the GDP deflator)
$\Delta A / A$	=	rate of productivity growth in the economy as a whole
$\Delta A_h / A_h$	=	rate of productivity growth in health care
b	=	labour share in health

Equation (3) says that price inflation in health equals economy wide inflation plus a Baumol effect. Combining equations (1) - (3) yields:

$$\frac{\Delta H}{H} - \frac{\Delta P}{P} = b(1+h)\left(\frac{\Delta A}{A} - \frac{\Delta A_h}{A_h}\right) + gZ \tag{4}$$

We define the ratio of labour productivity growth in health services to labour productivity growth in the overall economy as follows:

$$k \equiv \frac{\Delta A_h / A_h}{\Delta A / A} \tag{5}$$

Substitution of (5) into (4) yields:

$$\frac{\Delta H}{H} - \frac{\Delta P}{P} = b(1+h)(1-k)\frac{\Delta A}{A} + gZ \tag{6}$$

Equation (6) will be the basis for our econometric analysis. We will estimate variants of the following equation:

$$\frac{\Delta H}{H} - \frac{\Delta P}{P} = \delta \frac{\Delta A}{A} + \gamma Z + e\,, \tag{7}$$

where

$$\delta = b(1+h)(1-k)\,.$$

This yields an estimate for δ. We can combine the estimate for δ with exogenous information on b (the labour share in health care) and h (the price elasticity of demand for health care) in order to compute k in equation (6):

$$k^* = 1 - \frac{\delta}{b(1+h)} \tag{8}$$

Significance tests for k^* are based on the standard error of δ using the delta method. For the standard error of k^* we have:

$$\sigma_{k^*} = \sigma_{\delta} \frac{1}{b(1+h)} \tag{9}$$

Hence, in order to test the null hypothesis $k^* = 0$, we need to use the *t*-statistics defined as:

$$t_{k^*} = \frac{k^*}{\sigma_{k^*}}\,. \tag{10}$$

3 Data

We explore two data sources in the empirical analysis. The data on health expenditures are extracted from the OECD Health Data Base 2006, as well as gross domestic product (GDP) per capita, and population age 65 and over. The health expenditures are measured as the total health expenditures per capita, expressed in the National Currency Units (NCU)[1] at 2000 GDP price levels. GDP per capita series is also expressed in the NCU at 2000 GDP price levels. Population age 65 and over is expressed as a percentage of total population.

From the Groningen Growth & Development Centre (GGDC), we extract GDP per capita and GDP per hour worked (which is equivalent to labour productivity in the economy) series. Both series are expressed in 2006 US dollars, converted to 2006 price level with updated 2002 EKS[2] PPPs. GDP per capita is available for 42, while GDP per hour worked is available for 38 OECD and (candidate) EU member countries, plus Israel.

All series are extracted in the period 1970 to 2004, for the following sample of the OECD countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom and United States (23 in total)[3]. We express all series in 2006 US dollars, converted to 2006 price level with updated 2002 EKS PPPs[4]. Summary statistics and correlations between analysed series are presented in Tables 3.1 and 3.2.

As we can see from Table 3.1, we have an unbalanced panel of countries over the analysed time period (the largest sample size, if all observations are available, is 805). We can also see that GDP data from two sources (OECD & GGDC) have very similar summary statistics. From Table 3.2, we conclude that there exist high positive correlations between health expenditures and GDP per capita, GDP per hour worked, and population series. However, due to a very

[1] For the countries of the euro area (EMU), National Currency Units refer to national time series converted into euro by applying the irrevocable conversion rate between the national currency and the EUR. Thus, the evolution over time of all historical national series is preserved. It should, however, be noted that this conversion does not transform a national into an international currency. For international comparisons, data in NCU still need to be converted into purchasing power parity (PPP) transformed values.

[2] The EKS method is a multilateral method developed by O. Elteto, P. Koves, and B. Schultz that computes the n^{th} root of the product of all possible Fisher indexes between *n* countries. It has been used at the detailed heading level to obtain heading parities, and also at the GDP level. EKS has the properties of base-country invariance and transitivity. It is the method used by Eurostat and the OECD to calculate PPPs for basic headings and to aggregate basic heading PPPs to obtain PPPs for each level of aggregation up to and including GDP. Within the context of Eurostat-OECD comparisons, EKS results are considered to be better suited to comparisons across countries of the price and volume levels of individual aggregates. For more detailed definition, see the OECD glossary of statistical terms: http://stats.oecd.org/glossary/detail.asp?ID=5525

[3] We also estimate results for a smaller sample of 14 EU countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, United Kingdom), plus the United States. See section 4 below.

[4] First, we convert series from the OECD data base expressed in NCU at 2000 GDP price levels, to a 2006 price base using OECD consumer price indices for 2006. Once series are expressed in 2006 prices, we divide them by the GDP PPPs available from the GGDC web site, in order to get all series in 2006 US dollars. Plots of the two GDP per capita series, one from the GGDC data base and the other from the OECD data base, both expressed in 2006 US dollars, are to be found in the Appendix.

strong trendy behaviour of both health expenditures and GDP series[5], simply running an OLS regression would produce spurious estimation results.

Table 3.1 Summary statistics: sample size, mean, standard deviation, min, and max

Variable	Observation	Mean	Std. Dev.	Min	Max
he	747	1931.57	889.36	226.63	6548.23
gdph	786	31.80	9.59	10.96	61.84
gdp^1	805	24520	7227	8540	60080
gdp^2	786	24695	7558	8538	62076
pop	801	13.27	2.42	7.1	19.5
lhe	747	7.46	0.48	5.42	8.79
lgdph	786	3.41	0.32	2.39	4.12
$lgdp^1$	805	10.06	0.30	9.05	11.00
$lgdp^2$	786	10.07	0.31	9.05	11.04
lpop	801	2.57	0.19	1.96	2.97

Note: he = health expenditures per capita; gdph = GDP per hour worked; gdp = GDP per capita (gdp^1 = OECD source; gdp^2 = GGDC source); pop = population age 65 and over; with prefix l for the ln transformation.

Table 3.2 Correlation coefficients (series in levels and ln transformed)

Variable	he	gdph	$gdp^{(1)}$	$gdp^{(2)}$	pop
he	1.000				
gdph	0.741	1.000			
gdp^1	0.858	0.853	1.000		
gdp^2	0.822	0.888	0.986	1.000	
pop	0.375	0.541	0.361	0.393	1.000
	lhe	lgdph	$lgdp^{(1)}$	$lgdp^{(2)}$	lpop
lhe	1.000				
lgdph	0.822	1.000			
$lgdp^1$	0.909	0.874	1.000		
$lgdp^2$	0.887	0.907	0.988	1.000	
Lpop	0.452	0.579	0.404	0.449	1.000

Note: he = health expenditures per capita; gdph = GDP per hour worked; gdp = GDP per capita (gdp^1 = OECD source; gdp^2 = GGDC source); pop = population age 65 and over; with prefix l for the ln transformation.

[5] Graphs of the analysed series are presented in the Appendix.

4 Estimation results

Following the approach of the recent paper by Lichtenberg (2007), we estimate equation (7) in two different ways. In the first approach, we use all available data to estimate the following equation:

$$\ln H_{it} = \beta \ln A_{it} + \gamma \ln Z_{it} + \alpha_i + \varepsilon_{it} \tag{11}$$

where H_{it} is a natural logarithm of health expenditures per capita in a country *i*, in a year *t*; A_{it} is a natural logarithm of the GDP per hour worked and it is a measure of labour productivity in the economy as a whole, in a country *i*, in a year *t*; Z_{it} is a vector of covariates, which consists of GDP per capita and population age 65 and over, in country *i* and year *t*; α_i captures unobserved country effects, and ε_{it} is a random error term. Estimation results of this first estimation approach are presented in Table 4.1.

Table 4.1 Estimates of equation (11): all available years

Variable	FE (1)	FE (2) (robust SEs)	FD (3)	FD (4) (robust SEs)
lgdph	0.192	0.192		
	(0.070)***	(0.205)		
$lgdp^2$	1.206	1.206		
	(0.072)***	(0.280)***		
lpop	0.458	0.458		
	(0.052)***	(0.280)		
dlgdph			0.499	0.499
			(0.097)***	(0.157)***
$dlgdp^2$			0.449	0.499
			(0.093)***	(0.127)***
dlpop			0.788	0.788
			(0.126)***	(0.146)***
Observations	725	725	695	695
Number of countries	23	23		

Note: he = health expenditures per capita; gdph = GDP per hour worked; gdp = GDP per capita (gdp^2 = GGDC source); pop = population age 65 and over; with prefix l for the ln transformation; with prefix d for the first-difference transformation; standard errors in parentheses; * p<0.1; ** p<0.05; *** p<0.01.

Table 4.1 shows in columns (1) and (2) the within estimation results (FE) of equation (11), without and with robust standard errors[6]; columns (3) and (4) show OLS estimation results of equation (11) expressed in first differences (FD), without and with robust standard errors. If our model is correctly specified, the within and the 'first-difference' estimation procedures should yield similar estimates for the parameters β and γ (Verbeek, 2004). The only difference should be in the estimated standard errors.

[6] Newey-West standard errors.

The error term of equation (11) might follow a first-order autoregressive process:

$$u_{it} = \rho u_{it-1} + \xi_{it}$$

where ξ_{it} is a white noise term. We performed Breusch-Godfrey test on autocorrelation, which tests the following hypothesis $H_0 : \rho = 0$. However, we cannot reject H_0 of no autocorrelation in the error term, either for the within or the model in first differences. Nevertheless, we re-estimated both models with robust standard errors, which are robust to the presence of both autocorrelation and heteroscedasticity.

Our estimated robust standard errors are larger than the non-robust ones, which usually indicates that there is a slight positive autocorrelation in the error term. Further, our estimates of β and γ are dramatically different between the within and the 'first-difference' estimation procedures. This difference might be due to the omitted variable bias or to the fact that our exogenous variables are not strictly exogenous.

We also follow the second approach of Lichtenberg (2007), and estimate equation (11) in the 'long-difference' form (12):

$$\ln H_{iT} - \ln H_{ik} = \beta(\ln A_{iT} - \ln A_{ik}) + \gamma(\ln Z_{iT} - \ln Z_{ik}) + (\varepsilon_{iT} - \varepsilon_{ik}) \tag{12}$$

where *T* and *k* correspond to different time periods in the sample. Since we base our estimation results on observations at the end of 17-, 10- and 5-year periods respectively, there cannot be serial correlation[7]. Columns (1) to (3) in Table 4.2 show estimation results for different long-difference periods. In column (1), we have two observations per country[8], using data for k_1 = 1970 and T_1 = 1987, and k_2 = 1988 and T_2 = 2004. Columns (2) and (3) show estimation results for 10- and 5-year long-difference periods respectively.

[7] Similar to the approach in Lichtenberg (2007) approach, we have also estimated equation (12) using data only for the first (*k* = 1970) and last (*T* = 2004) years of the sample period. However, due to the missing observations and a small number of countries, our sample shrinks to only 14 observations, rendering estimation impossible.

[8] The sample size is smaller than 46 due to missing observations for some years, for some countries, for some covariates.

Table 4.2	**Estimates of equation (12): 'long-difference' estimation procedure**		
Variable	LD (1)	LD (2)	LD (3)
	1970, 1987; 1988, 2004	1970, 1979; 1980, 1989; 1990, 1999; etc.	five-year periods 1970, 1974; 1975, 1979; etc.
lgdph	0.308	0.600	0.462
	(0.255)	(0.251)**	(0.140)***
lgdp$^{(2)}$	1.276	0.913	0.953
	(0.279)***	(0.262)***	(0.139)***
Lpop	0.345	0.327	0.150
	(0.256)	(0.207)	(0.186)
Observations	32	75	135

Note: he = health expenditures per capita; gdph = GDP per hour worked; gdp = GDP per capita (gdp^2 = GGDC source); pop = population age 65 and over; with prefix l for the ln transformation; standard errors in parentheses; * p<0.1; ** p<0.05; *** p<0.01.

Looking at the estimation results in columns (1) to (3) in Table 4.2, we conclude that labour productivity in the economy as a whole has a positive and significant effect on health expenditures per capita. The size of this coefficient ranges from 0.3 (column 1) to 0.6 (column 2). Since the sample size in column (1) is relatively small and the estimated coefficient on labour productivity is not significant, we believe that the size of this coefficient is between 0.5 and 0.6. Comparing estimation results in Table 4.2 to the 'first-difference' estimation results in Table 4.1 (estimated coefficient for labour productivity is 0.5), the size of the estimated coefficient in Table 4.2 seems plausible.

The estimated coefficient on GDP per capita is significant and around one (also for the smaller sample of countries), which is comparable to the estimation results of Mot and Van Elk (2007). However, our estimated standard errors are larger due to the small size of our sample. The estimated coefficient of population age 65 and over is not significant in all long-difference specifications (also for the smaller sample of countries).

Checking our results for robustness, we re-estimated equations (11) and (12) using a smaller sample of countries (14 EU countries, plus USA), shortening the sample, so that we drop the first and last observations of the whole sample period (t = 1970 and t = 2004, respectively), and estimating results without France, Greece, and Italy. Explanation for the three additional sample specifications is as follows. First, 14 EU countries, plus USA are a more homogenous group of countries (in terms of GDP per capita) than full the sample of 23 OECD countries. Second, for some countries like Australia, Belgium, Denmark, Japan, Germany and the Netherlands, data on health expenditures are missing at the first and/or the last observations. Third, France, Greece, and Italy have large chunks of health expenditure data missing.

The robustness checks are presented in the Appendix. The estimated results for all three sample specifications are robust if we look at the 'first-difference' estimations in Tables 8.1, 8.3, and 8.5 respectively, suggesting a size of the coefficient next to labour productivity of around 0.5. However, if we look at the ‘long-difference’ estimation results, the estimated coefficient is around 0.4 for the sample of 14 EU, plus USA countries (Table 8.2), around 0.7 if we drop the first and the last observations of the whole sample period (Table 8.4), and around 0.5 if we look at the full sample of countries, without France, Greece, and Italy (Table 8.6). Hence, we conclude that labour productivity in the economy as a whole has a large, positive and significant effect on health expenditures per capita. The estimated effect ranges from 0.4 to 0.7.

5 Productivity growth in health care

The estimation results presented in the previous section are consistent with a large Baumol effect in health spending. The Baumol effect arises because productivity growth in the economy as a whole translates into wage growth in all sectors of the economy, including the sectors that lag behind in productivity growth (Baumol and Bowen (1966)). This raises relative prices in these lagging sectors. If demand is inelastic, this will result in a rise in real spending on goods and services produced in lagging sectors. This seems to apply to health care in the panel of countries included in our analysis.

In order to determine by how much labour productivity growth in health care lags behind overall productivity growth, we employ equations (8) – (10). For this calculation, we use the estimate for δ presented in the final column of Table 4.2. We also need information on the labour share of health care and on the price elasticity of demand for health.

Data on the labour share in health care are not readily available. However, the Groningen Growth and Development Centre (GGDC) maintains an Industry Growth Accounting Database which contains data on the labour share in various sectors of the economy for Australia, Canada, France, Germany, the Netherlands, the United Kingdom and the United States.[9] One of the sectors covered by the database is non-market services, which includes most of health care.[10] According to these data, the labour share of non-market services is about 0.8. We will take this as our central estimate and perform sensitivity analysis using 0.7 and 0.9.

Estimates for the price elasticity of demand for health from the literature have recently been surveyed in Ringel et al. (2002). The authors summarize their findings as follows: "Despite a wide variety of empirical methods and data sources, the estimates of the demand for health care [..] are consistently found to be price inelastic. Although the range of price elasticity estimates is relatively wide, it tends to centre on –0.17, meaning that a one percent increase in the price of health care will lead to 0.17 percent reduction in health care expenditures." (Ringel et al. (2002), p. 20). We will use –0.2 as our central estimate and again perform sensitivity analysis around this value.

Calibration results are presented in Table 5.1. According to our central estimate corresponding to a labour share of 0.8 and a price elasticity of demand of –0.2, labour productivity in health care was 20% of labour productivity in the overall economy. Moreover, this value does not differ significantly from zero. Sensitivity analyses around these values indicate that this conclusion remains valid for other values of the parameters, except for the

[9] The database can be accessed at www.ggdc.net.

[10] According to the OECD national accounts definition, non-market services include general public services, non-market services of education and research provided by general government and private non-profit institutions, non-market services of health provided by general government and private non-profit institutions, domestic services and other non-market services n.e.c. (http://stats.oecd.org/glossary/detail.asp?ID=1814).

combination of very low demand elasticities and a very high labour share. In this case, labour productivity in health care amounts to 40% of labour productivity in the overall economy, and it is statistically significantly different from zero.

Table 5.1 Labour productivity in health care as a fraction of labour productivity in the overall economy

Demand elasticity	Labour share		
	0.7	0.8	0.9
– 0.1	0.2	0.3	0.4
	(0.9)	(1.6)	(2.2)
– 0.2	0.1	0.2	0.3
	(0.4)	(1.0)	(1.6)
– 0.3	0	0.1	0.2
	(– 0.1)	(0.4)	(0.9)

Note: based on equations 6-8, using the estimated coefficients in the final column of Table 4.2; t-values in parentheses.

The findings reported in Table 5.1 may be compared with recent quality-adjusted estimates of medical productivity in the US reported in Triplett ad Bosworth (2003). They find for the US that labour productivity in health services rose by 0.7 percent per year in the period 1995-2000, a sharp break with the measured fall in labour productivity in health care in the years before 1995. They argue that this break reflects improved measured methods rather than a real change in productivity. For the whole (non-farm) US-economy they report 2.6% annual labour productivity growth. Thus, labour productivity in health care rose 0.27 times as rapid as labour productivity in the economy as a whole. This is quite consistent with the values in Table 5.1 that correspond to low a price elasticity of demand and/or a high labour share.

6 Conclusions

In this paper, we study the Baumol effect in health spending, using a panel data set of OECD countries. We try to answer two questions:

1. How large is the Baumol effect in health care?
2. What does the estimated Baumol effect say about the amount cost-reducing technological change in health care?

We address the first question by regressing real health spending on real income and overall productivity growth in the economy as measured by the real GDP per hour worked. We find large effects of labour productivity growth in the overall economy on real health spending. One percentage growth in economy-wide labour productivity is associated to with about 0.5 percent growth in real health spending. As far as we know, this is a novel empirical finding. The implication of this finding is that the Baumol effect is important, a conclusion that agrees with recent research by Nordhaus (2006) for other sectors of the economy.

In order to answer the second question, we interpret the estimated Baumol effect as a reduced form coefficient of a structural model in which real health spending is determined by the relative price per unit of health care of constant quality, the price elasticity of demand, income per capita and demographic shifters. We assume that the relative price per unit of health care of constant quality is solely determined by the Baumol effect. We find that labour productivity in health care was about one fifth as high a labour productivity in the overall economy.

It should be noted that our regression design is very simple. Extensions of the empirical approach would include testing for the nonstationarity of the analysed series and performing panel data unit root and cointegration tests (for more details, see Verbeek (2004), chapter 10.6). It would also be interesting to estimate multivariate unobserved components model, where technology progress would be modelled as an unobserved state variable. For an application of this approach to the financial data, see Menkveld, Koopman and Lucas (2007).

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Appendix

A1 Robustness checks

A1.1 Estimation results for a smaller sample of countries (14 EU countries, plus USA)

Table A1.1 Estimates of equation (11): all available years

Variable	FE (1)	FE (2) (robust SEs)	FD (3)	FD (4) (robust SEs)
lgdph	0.176	0.176		
	(0.082)**	(0.298)		
$lgdp^2$	1.028	1.028		
	(0.089)***	(0.368)**		
lpop	0.868	0.868		
	(0.079)***	(0.323)**		
dlgdph			0.565	0.565
			(0.111)***	(0.175)***
$dlgdp^2$			0.450	0.450
			(0.110)***	(0.144)***
dlpop			0.742	0.742
			(0.152)***	(0.162)***
Observations	449	449	427	427
Number of countries	15	15		

Note: he = health expenditures per capita; gdph = GDP per hour worked; gdp = GDP per capita (gdp^2 = GGDC source); pop = population age 65 and over; with prefix l for the ln transformation; with prefix d for the first-difference transformation; standard errors in parentheses; * p<0.1; ** p<0.05; *** p<0.01.

Table A1.2 Estimates of equation (12): 'long-difference' estimation procedure

Variable	LD (1)	LD (2)	LD (3)
	1970, 1987; 1988, 2004	1970, 1979; 1980, 1989; 1990, 1999; etc.	five-year periods 1970, 1974; 1975, 1979; etc.
lgdph	0.369	0.431	0.334
	(0.319)	(0.319)	(0.168)*
$lgdp^2$	1.063	1.069	1.025
	(0.368)**	(0.354)***	(0.173)***
lpop	0.543	0.328	0.168
	(0.357)	(0.296)	(0.265)
Observations	20	47	83

Note: he = health expenditures per capita; gdph = GDP per hour worked; gdp = GDP per capita (gdp^2 = GGDC source); pop = population age 65 and over; with prefix l for the ln transformation; standard errors in parentheses; * p<0.1; ** p<0.05; *** p<0.01.

A1.2 Estimation results for a shorter sample period, that is, without the first and the last observations of the sample period (t = 1970 and t = 2004, respectively)

Table A1.3 Estimates of equation (11): all available years, less 1970 & 2004

Variable	FE (1)	FE (2) (robust SEs)	FD (3)	FD (4) (robust SEs)
lgdph	0.147	0.147		
	(0.072)**	(0.201)		
lgdp^2	1.209	1.209		
	(0.074)***	(0.259)***		
lpop	0.483	0.483		
	(0.053)***	(0.279)*		
dlgdph			0.487	0.487
			(0.098)***	(0.160)***
dlgdp^2			0.404	0.404
			(0.094)***	(0.120)***
dlpop			0.825	0.825
			(0.127)***	(0.149)***
Observations	691	691	663	663
Number of countries	23	23		

Note: he = health expenditures per capita; gdph = GDP per hour worked; gdp = GDP per capita (gdp^2 = GGDC source); pop = population age 65 and over; with prefix l for the ln transformation; with prefix d for the first-difference transformation; standard errors in parentheses; * p<0.1; ** p<0.05; *** p<0.01.

Table A1.4 Estimates of equation (12): 'long-difference' estimation procedure

Variable	LD (1)	LD (2)	LD (3)
	1971, 1986; 1987, 2003	1971, 1981; 1982, 1992; 1993, 2003	Five-year periods 1971, 1975; 1976, 1980; etc.
lgdph	0.282	0.747	0.753
	(0.237)	(0.212)***	(0.180)***
lgdp^2	1.246	0.757	0.620
	(0.253)***	(0.206)***	(0.174)***
lpop	0.365	0.350	0.378
	(0.218)	(0.200)*	(0.219)*
Observations	38	60	143

Note: he = health expenditures per capita; gdph = GDP per hour worked; gdp = GDP per capita (gdp^2 = GGDC source); pop = population age 65 and over; with prefix l for the ln transformation; standard errors in parentheses; * p<0.1; ** p<0.05; *** p<0.01.

A1.3 Estimation results for a smaller sample of countries (without France, Greece, and Italy)

Table A1.5 Estimates of equation (11): all available years

Variable	FE (1)	FE (2) (robust SEs)	FD (3)	FD (4) (robust SEs)
lgdph	0.165	0.165		
	(0.074)**	(0.213)		
$lgdp^2$	1.227	1.227		
	(0.075)***	(0.282)***		
lpop	0.465	0.465		
	(0.054)***	(0.285)		
dlgdph			0.541	0.541
			(0.100)***	(0.160)***
$dlgdp^2$			0.424	0.424
			(0.096)***	(0.132)***
dlpop			0.765	0.765
			(0.131)***	(0.146)***
Observations	670	670	649	649
Number of countries	20	20		

Note: he = health expenditures per capita; gdph = GDP per hour worked; gdp = GDP per capita (gdp^2 = GGDC source); pop = population age 65 and over; with prefix l for the ln transformation; with prefix d for the first-difference transformation; standard errors in parentheses; * p<0.1; ** p<0.05; *** p<0.01.

Table A1.6 Estimates of equation (12): 'long-difference' estimation procedure

Variable	LD (1)	LD (2)	LD (3)
	1970, 1987; 1988, 2004	1970, 1979; 1980, 1989; 1990, 1999; etc.	five-year periods 1970, 1974; 1975, 1979; etc.
lgdph	0.348	0.643	0.468
	(0.259)	(0.262)**	(0.141)***
$lgdp^2$	1.241	0.868	0.964
	(0.281)***	(0.272)***	(0.140)***
lpop	0.398	0.331	0.091
	(0.265)	(0.221)	(0.192)
Observations	30	69	127

Note: he = health expenditures per capita; gdph = GDP per hour worked; gdp = GDP per capita (gdp^2 = GGDC source); pop = population age 65 and over; with prefix l for the ln transformation; standard errors in parentheses; * p<0.1; ** p<0.05; *** p<0.01.

A2 Graphs

Figure A2.1 GDP p/c from the two data sources (OECD & GGDC)

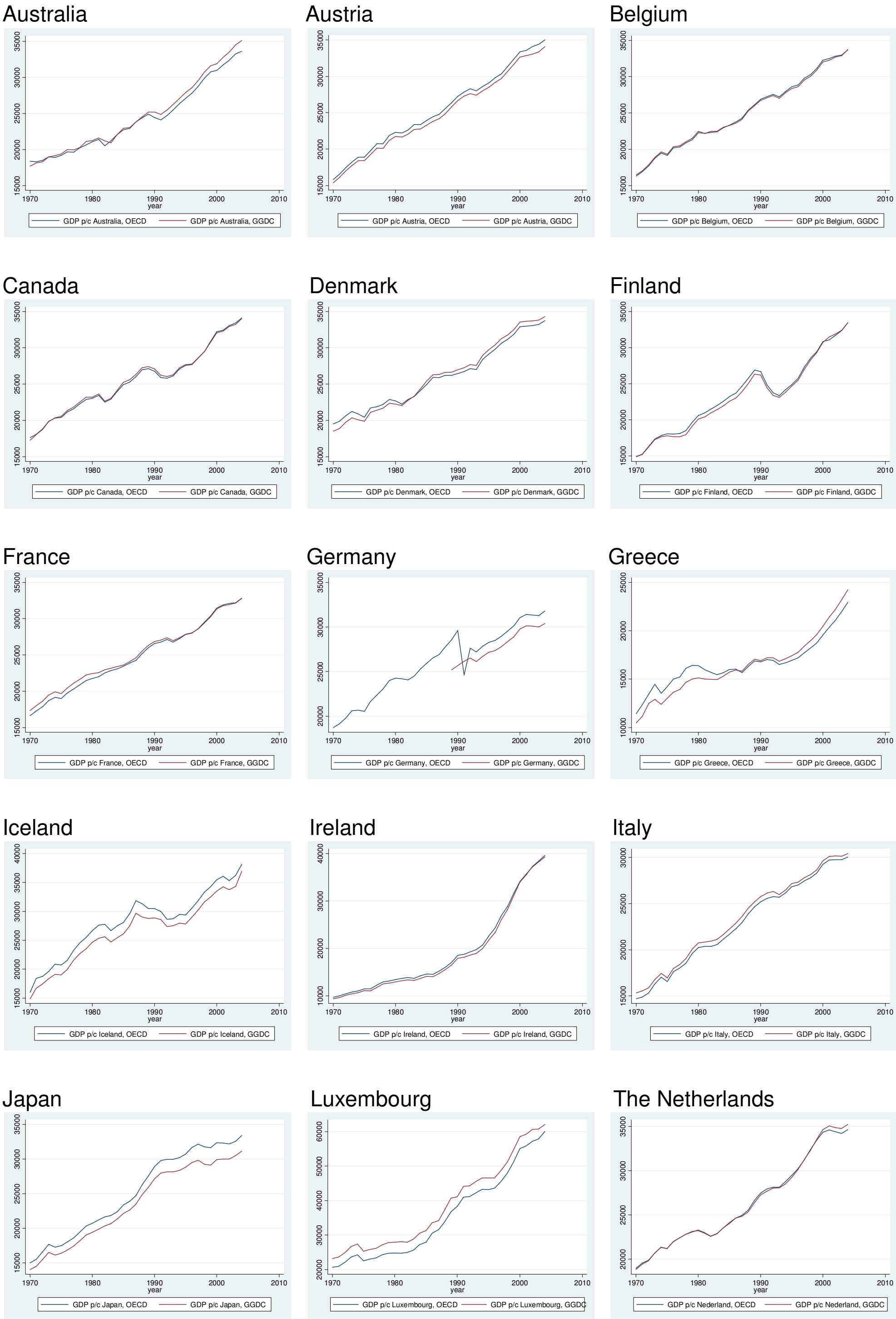
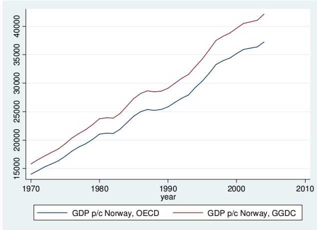


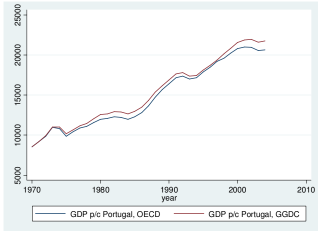
Figure A2.1 Continued

New Zealand

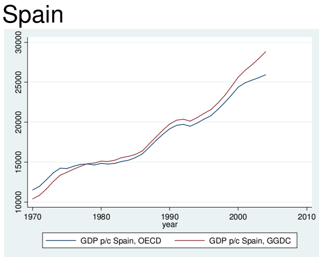
Norway



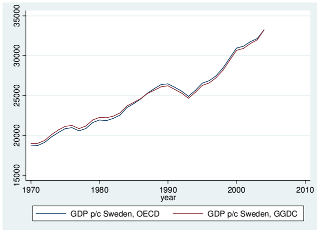
Portugal



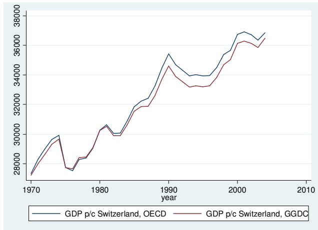
Spain



Sweden



Switzerland



UK

USA

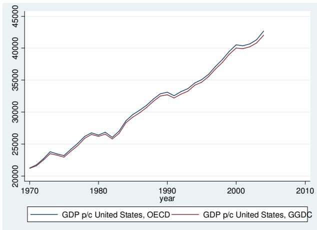


Figure A2.2 Total health expenditures p/c series, expressed in the 2006 US dollars, converted to 2006 price level with updates 2002 EKS PPPs

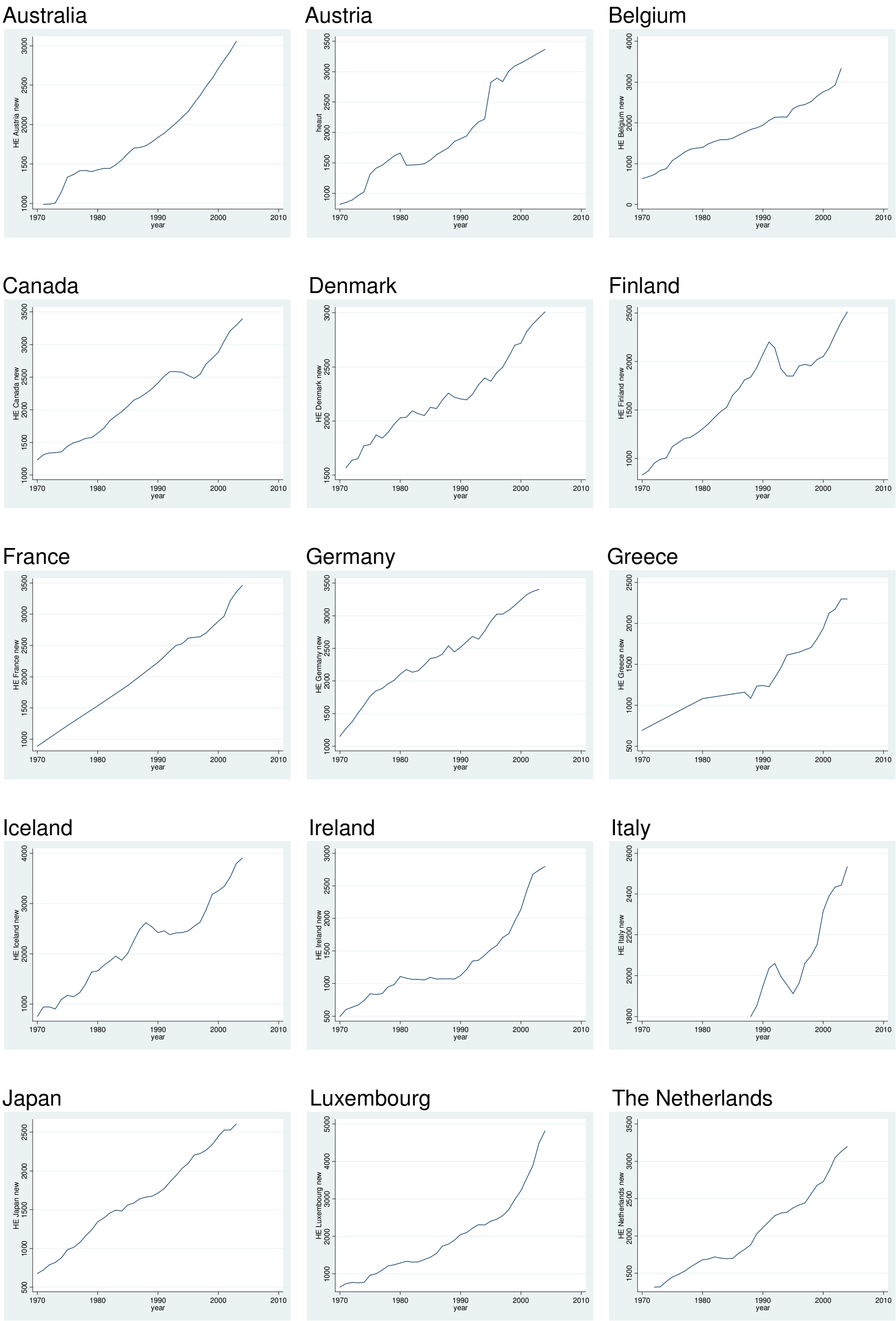
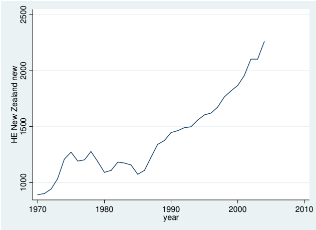
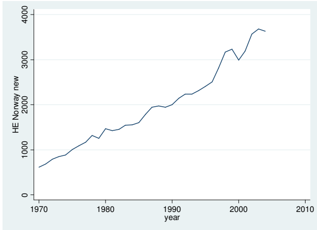


Figure A2.2 Continued

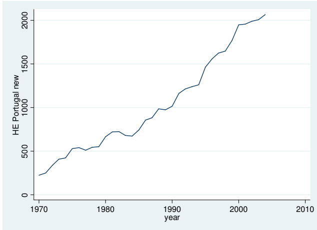
New Zealand



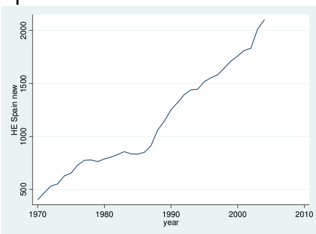
Norway



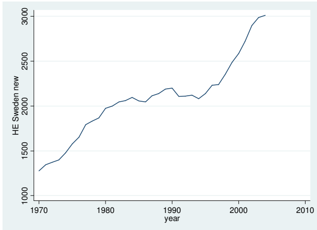
Portugal



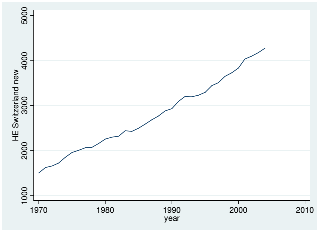
Spain



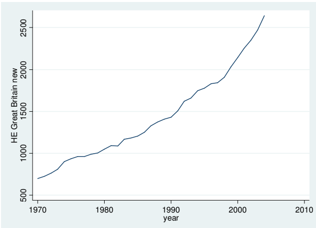
Sweden



Switzerland



UK



USA