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Pathways and Hidden Benefits of Healthcare Spending Growth in the U.S.

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Abstract After a brief reprieve, healthcare spending in the United States is expected to once again rise rapidly, continuing the trend of the past half-century. To inform the debate about whether policymakers should take action to contain high and rising medical care costs, we use panel data on all 50 states for the period 1993 to 2009 to estimate a healthcare spending model. Our framework, which includes a structural spending equation and a health production function, identifies the pathways through which medical technology and income affect healthcare costs and the potential health benefits they produce. We find evidence that medical technology and income are important factors fueling rising healthcare costs in the United States. However, our results also indicate they generate large health benefits in the form of lower mortality that may outweigh the costs and increase social economic welfare.

Keywords Healthcare spending · Medical technology · Income · Cost-benefit analysis

JEL Classification I10 · I18

Introduction

Annual healthcare spending in the United States is approaching $3 trillion, continuing its decades-long upward trend. Spending on medical care now accounts for more than 17 % of the gross domestic product, a substantially higher share than in the 1960s when it was a mere 5 %. While the rate of growth in recent years has slowed relative to the late 1990s and early 2000s, largely due to the slowing economy, healthcare spending is expected to increase faster

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than national income in the foreseeable future. However, simply uncovering the drivers of medical care spending and reducing their impact through policy interventions may not be socially desirable if such reductions have a detrimental effect on population health.

Most prior studies on healthcare spending employ two alternative approaches. One involves analyzing individual-level data to explain factors that affect Medicare or hospital spending. The other utilizes country-level data and analyzes spending per capita across nations (Sirovich et al. 2008; Sutherland et al. 2009; Zuckerman et al. 2010; Gerdtham and Jonsson 2000). However, relatively few researchers use state-level panel data to draw conclusions about healthcare spending (Di Matteo 2005; Rettenmaier and Saving 2009; Rettenmaier and Wang 2012; Cuckler et al. 2011; Cuckler and Sisko 2013). In general, previous studies find evidence that advancements in medical technology and rising incomes are important factors driving the growth in healthcare spending. Many economists and policymakers argue that the resultant spending growth is a social problem because it makes health insurance and medical care less affordable, which has an adverse effect on population health. Some also maintain that curbing the adoption of expensive new technologies may help contain costs that are deemed unsustainable in the long run (CBO 2008). However, studies from which these conclusions are drawn do not account for the possibility that both rising incomes and new technologies simultaneously lead to improvements in health. An increase in population health has both an offsetting effect on healthcare costs and produces benefits for society as people are healthier and live longer. It is therefore possible that even though rising incomes and advances in technology drive healthcare spending up, they may produce benefits that outweigh the costs.

The objective of our study is to estimate the effect of income and technology on the behavior of personal healthcare spending over time in the U.S., while simultaneously exploring how much spending is offset by improvements in population health. We compare the cost of spending growth arising from income growth and technological advancements to the concomitant health benefit to evaluate the impact on social economic welfare. To our knowledge, our study is the first to adopt this approach to analyzing healthcare spending. Our study uses panel data on all 50 states for the period 1993 to 2009.

Empirical Model and Strategy

Our empirical model consists of a structural healthcare spending equation (1) and a health production function (2) given by[1]

$$S_{it} = \beta_H H_{it} + \beta_T T_t + \beta_I I_{it} + \beta_X X_{it} + \beta_Y Y_{it} + \gamma_i + \mu_{it} \quad (1)$$

$$H_{it} = \alpha_S S_{it} + \alpha_T T_t + \alpha_I I_{it} + \alpha_X X_{it} + \alpha_Z Z_{it} + \lambda_i + \varepsilon_{it} \quad (2)$$

where the subscripts i and t denote state and year; S_{it} is healthcare spending; H_{it} is population health status; T_i is medical technology; I_{it} is income; X_{it}, Y_{it}, and Z_{it} are vectors of exogenous variables other than income and technology; γ_i is a state-specific effect on healthcare spending; λ_i is a state-specific effect on population health; and μ_{it}

[1] For a detailed description of the theoretical framework, see Thornton and Rice (2008), Appendix.

and ε_{it} are error terms. All quantitative variables defined below are in logarithmic form, so their estimated marginal effects are elasticities. Our model is a modification of the one estimated by Thornton and Rice (2008).

The variable of interest is real personal healthcare spending per capita expressed in constant 2009 dollars (*S*). A potentially important factor affecting spending is population health status, which is measured by the crude death rate per 100,000 population (*H*).[2] We expect states with healthier populations to have lower death rates, demand less medical care, and have lower healthcare spending. We also expect states that utilize less medical care to have less healthy populations, higher death rates, and utilize more medical care. This simultaneous causation between spending and health is captured by the system of two structural equations and allows us to analyze two pathways through which income and technology may affect health spending. Both factors may have a direct effect on spending by influencing the demand or supply of medical care for a given state of health, and an indirect effect on spending by affecting health and medical care demand.[3]

It is widely recognized that income growth and advances in medical technology increase aggregate healthcare spending through their direct effects on the demand and supply of medical care. However, there is mounting evidence that the development and diffusion of new medical technologies and rising incomes over the past several decades have also produced substantial improvements in health outcomes. A number of studies conclude that much of the improvement in the heart disease mortality rate and mortality rates for various other diseases can be attributed to new diagnostic tests and treatments arising from the growing stock of biomedical knowledge (Braunwald 1997; Cutler et al. 1999; Cutler and Kadiyala 2003; Thornton 2011). A growing body of research also finds evidence of a significant reduction in mortality associated with increased incomes. People with higher incomes are more likely to have better material conditions, more social support, higher social status, a greater sense of control over their environment, and lower stress levels, all of which affect health positively (Smith 1999; Deaton 2002; Marmot 2002). This suggests that rising incomes and advances in medical technology may have both a direct positive effect on healthcare spending by increasing the demand and decreasing the supply of medical care, and an indirect negative effect on spending by improving health and lowering the demand for and utilization of medical care. Theoretically, the total effect of income and technology on healthcare spending may be positive, negative, or zero depending upon the relative size of the direct and indirect effects.

We measure income (*I*) by real personal income per capita in constant 2009 dollars. The direct effect of income on healthcare spending is measured by the coefficient of income in the spending equation, $\beta_{I.}$ The indirect effect is measured by the product of the coefficient of income in the health production function and the coefficient of health in the structural spending equation, α_I*β_H.

Advancements in medical technology can be loosely defined as the change in the stock of medical knowledge that allows treatment of health-related problems, the development of new drugs, diagnostic tests, and medical devices, as well as the

[2] Population health comprises both duration and quality of life. Like prior aggregate health production function studies, we adopt a length-of-life measure.

[3] Past studies estimate the parameters of a reduced-form aggregate healthcare spending equation obtained by substituting the health production function (2) into the structural spending equation (1), and therefore cannot identify the pathways through which variables affect spending.

improved application of existing services. Estimating technological progress is challenging since it cannot be measured directly. To capture the effects of medical technology, most prior studies have used either a residual approach, various technological indicators, or a time trend. The residual approach attempts to identify all important factors that affect spending and estimates their individual contribution to spending growth for a specific time period. The unexplained portion of spending growth, or the residual, is interpreted as technology's contribution (J. P. Newhouse 1992; D. Cutler 1995; Peden and Freeland 1998; Abrantes-Metz 2012). As a more direct measure of technology, some studies use indicators such as research and development (R&D) spending, patent applications, and innovation expenditures. However, estimates of technology's effect on spending vary substantially depending on the choice of indicator.

Kleinknecht et al. (2002) argue that common technological indicators such as R&D costs and patent applications have severe shortcomings and are weakly correlated. Given the complexity and scope of medical progress, it is unlikely that using a narrow technological indicator will accurately capture the overall technological change. Some recent studies attempt to capture technology with a linear time trend (Cuckler et al. 2011; Cuckler and Sisko 2013; Chen et al. 2014). However, imposing a linear structure on technology may be unduly restrictive, since it is unlikely to progress at a constant rate. We choose to follow the panel-data approach of Di Matteo (2005); Smith et al. (2009) and Thornton (2011) by replacing the unobserved technology variable (T) by a set of yearly dummy variables. Since rapidly diffusing medical technology should affect states equally but vary from year to year, we believe it will be captured reasonably well by the time effects in our panel data model. We recognize that the time effects will capture other unobserved time-dependent factors such as changes in medical prices relative to the prices of other goods and services, administrative costs, and various structural changes. However, like prior studies that have used this approach, we believe technology is the dominant component, and like Di Matteo (2005) we interpret the time effects as an upper-bound estimate of the contribution of medical innovation to healthcare spending growth.[4] This approach to capturing technology is especially appropriate at the state level since, unlike countries, states are relatively homogeneous in terms of human capital and federal regulations, allowing new technologies to be easily adoptable and quickly diffused. We measure the total direct contribution of technology to spending growth by the exponentiated 2009 time coefficient in the structural spending equation, designated $\beta_{T17,}$ which represents the entire 17-year period. To measure the indirect effect of innovation on spending that works through health improvements, we use the product of the exponentiated time coefficient in the health production function and coefficient of health in the structural spending equations, $\alpha_{T17*}\ \beta_H$.

The exogenous variables in vector Y include the percent of the population covered by Medicare, Medicaid, non-HMO health plans, and health insurance, as well as the number of doctors and hospital beds per capita. We maintain that those factors have a direct effect only on healthcare expenditures via the structural spending equation, and therefore are excluded from the health production function. For example, individuals in states with higher public and private insurance coverage have a greater ability to pay for

[4] Baltagi and Griffin (1988) discuss in detail the history of using time trends and time dummy variables to describe technical change in econometric literature.

healthcare, and may demand and utilize more. In turn, the increased spending on medical care (S) will indirectly affect health. The number of doctors and hospital beds are excluded from the health production function because they do not have a direct effect on health. Rather, doctors and hospitals affect health indirectly by the services they provide, measured by S.[5]

We maintain that exogenous variables in vector Z have an indirect effect on health expenditures only through their effect on the health status of the population. These include the following variables in the health production function: gallons of wine, spirits and beer consumed per capita, packs of cigarettes sold per capita, and percent of state population age 18 and older with a Body Mass Index (BMI) ≥ 30.0.[6] Because higher incidence of illness and disease in the elderly population results in greater utilization of medical care, and therefore, higher spending, we include the percent of the state population 65 years of age and older in the health production function.

Finally, we maintain that the exogenous variables in vector X potentially have both direct and indirect effects on healthcare spending, and therefore include them in both equations. Prior studies find evidence that education has an effect on both health and spending through its impact on people's awareness of lifestyle choices, illness, and medical care (Grossman 2003; Thornton and Rice 2008). We include unemployment and population density to control for the effect of such factors as economic conditions, access to medical care, pollution, and congestion. Race and gender control for compositional state characteristics. The fixed effects (γ_i and λ_i) are included to account for unobserved heterogeneity across states, which may include differences in lifestyle, environment, and health stock endowments.

Our empirical strategy is as follows. We estimate each of our two equations using an efficient two-step generalized method of moments (GMM) estimation procedure, which accounts for the endogeneity of health and medical care spending, and possible presence of serial correlation and heteroscedasticity. Our analytical framework indicates that variables in the health production function that are excluded from the spending equation will have an indirect effect on healthcare spending only through their effect on health. Thus, we use the variables in vector Z as instruments to identify the healthcare spending equation. We identify the health production function by the set of variables in vector Y in the spending equation. We maintain that these variables will only have an indirect effect on health through their effect on medical care utilization and spending, and therefore can be legitimately excluded from the health production function. A detailed list of data sources, variable definitions, and descriptive statistics are provided in the Appendix.

Results

To test the relevance and exogeneity of instruments for both equations, we use a Hansen test of overidentifying restrictions and an F-test of the joint significance of

5 The direction of the effect will largely depend on the impact of more or fewer providers on supply conditions in the market for medical care and their willingness and ability to influence consumer demand for medical services.

6 BMI is defined as weight in kilograms divided by height in meters squared. BMI ≥ 30.0 indicates obesity.

identifying instruments in the first-stage regression. Together, these tests suggest that the instruments are valid and the model is correctly specified.[7] Coefficient estimates for the structural spending and health equations are presented in Table 1. Our estimates indicate that a doubling of per capita income increases spending directly by 27.7 % while lowering the state's mortality rate by 10.8 %. Advances in medical technology over this 17-year period increased direct spending by 41.7 % while reducing the mortality rate by 18.8 %. To further analyze the effect of technology, Table 2 presents the exponentiated yearly time coefficients for the structural spending equation and the health production function. We interpret these effects as technology's contribution to the spending growth and the mortality rate. All estimates are significant, have the expected signs, and display a pattern of rising magnitudes, indicating that technology was continuously driving up healthcare spending while lowering the mortality rate throughout the 17-year period. Column 2 coefficients represent the upper-bound estimates of the contribution of technology to spending growth for each year. The results indicate that while technology did not progress linearly, the overall technological progress displays an upward trend, indicating innovation's increasing contribution to the spending growth.

Because our estimate of the health elasticity indicates that a 10 % increase in mortality results in a 6.2 % increase in spending, any factor that affects health status has the potential to indirectly affect healthcare expenditures. For example, the estimate of the coefficient of technology indicates that medical innovation that occurred during the period 1993 to 2009 resulted in a 42 % increase in spending. However, our results show that advances in technology simultaneously lowered mortality, improved health, and therefore reduced spending on medical care indirectly. Therefore, to draw conclusions about the total effects of these factors on medical spending we need the measures of both direct and indirect effects, as shown in Table 3. As expected, we find that both income and technology have a significant offsetting effect on spending through mortality reductions. A 10 % increase in income lowers spending by 0.7 % through its positive effect on health. Between 1993 and 2009, improvements in health from advances in technology reduced healthcare spending by 12 %. The total effects, the sum of direct and indirect effects, are presented in column 4. Our calculations indicate that a 10 % increase in income resulted in a 2.1 % total increase in spending, while medical innovation that occurred during the period 1993 to 2009 increased medical care expenditures by 30 %.

The spending equation estimates in the second column of Table 1 indicate that eleven of twelve control variables have plausible signs, but only three are significant at the 5 % level. States with more providers, greater Medicaid, HMO, and total insurance coverage, higher unemployment, and relatively larger black, Hispanic, and female populations spend more on medical care, while those that are more educated and densely populated spend less. While Medicare has an unexpected sign, the large standard error indicates that the estimate is imprecise. This is likely the result of a high correlation with the elderly population. The health production function estimates

[7] The Hansen J statistics of 5.00 (p-value =0.17) and 4.25 (p-value =0.51) for the spending and health equations respectively provide evidence that the instruments used to identify both equations are exogenous. Additionally, the F-statistic of 39.41 (p-value <0.001) of the joint effect of identifying variables in the first-stage regression for the spending equation indicates that the instruments are strong. Similarly, the instruments used to identify the health production function are also jointly significant, with an F-statistic of 9.56 (p-value <0.001).

Table 1 Coefficient estimates

Variable	Structural spending equation	Standard error	Health production function	Standard error
Health (*H*)	0.618***	(0.112)		
Income	0.277***	(0.073)	−0.108**	(0.047)
Technology	0.417***	(0.058)	−0.188***	(0.036)
Education	−0.172**	(0.086)	0.034	(0.047)
Unemployment	0.022	(0.014)	−0.027***	(0.009)
Population density	−0.059	(0.057)	0.012	(0.042)
Black	0.082***	(0.022)	−0.031**	(0.012)
Female	0.753	(1.207)	−2.320**	(0.062)
Hispanic	0.032	(0.023)	0.002	(0.014)
Insurance	0.003	(0.067)		
Medicare	−0.003	(0.015)		
Medicaid	0.012	(0.009)		
Non-HMO coverage	0.040	(0.032)		
Physicians	0.398***	(0.090)		
Hospital beds	0.015	(0.009)		
Alcohol consumption			0.026	(0.032)
Cigarette consumption			0.024	(0.019)
Obesity			0.048***	(0.012)
Elderly			0.560***	(0.076)
Healthcare spending (*S*)			0.258***	(0.087)
Hansen J	5.00 (p-value =0.17)	4.25 (p-value =0.51)		
First-stage F-statistic	39.41 (p-value <0.001)	9.56 (p-value <0.001)		

The dependent variables are real personal healthcare spending per capita expressed in constant 2009 dollars (*S*) and crude death rate per 100,000 population (*H*). Number of observations = 846. Autocorrelation and heteroscedasticity consistent standard errors are in parentheses. Technology is the time dummy variable for year 2009. The omitted reference year for the time dummy variables is 1993. Identifying instruments for the spending equation are alcohol, cigarette, obesity, and elderly. Identifying instruments for the health production equation are insurance, Medicare, Medicaid, HMO, physicians, and hospital beds. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively. See Appendix for data sources.

presented in column 4 indicate that densely populated states with more elderly, obese, Hispanic, and educated populations, that consume more alcohol and cigarettes have higher mortality rates. States with higher unemployment and relatively larger female and black populations have lower death rates. Unlike many prior studies, our estimate of the effect of education is insignificant with an unexpected sign. However, this may be the result of our measure of education, which only distinguishes between those who do and do not have a high school degree.

Finally, while the estimate of healthcare spending in the production function appears to have an unexpected sign, it is consistent with a growing body of studies that distinguishes between the health effect of new medical technologies and greater intensity of healthcare services. While advances in technology have a large effect on

Table 2 Time effects

Year	Spending equation	Standard error	Health production function	Standard error
1994	0.010**	(0.004)	−0.020***	(0.003)
1995	0.023***	(0.007)	−0.027***	(0.006)
1996	0.030***	(0.010)	−0.040***	(0.009)
1997	0.048***	(0.015)	−0.052***	(0.012)
1998	0.063***	(0.021)	−0.059***	(0.015)
1999	0.076***	(0.023)	−0.055***	(0.018)
2000	0.100***	(0.025)	−0.063***	(0.021)
2001	0.138***	(0.028)	−0.074***	(0.024)
2002	0.188***	(0.032)	−0.081***	(0.028)
2003	0.232***	(0.036)	−0.094***	(0.031)
2004	0.300***	(0.041)	−0.134***	(0.032)
2005	0.313***	(0.042)	−0.129***	(0.034)
2006	0.345***	(0.047)	−0.152***	(0.035)
2007	0.361***	(0.052)	−0.168***	(0.036)
2008	0.349***	(0.052)	−0.162***	(0.035)
2009	0.417***	(0.058)	−0.188***	(0.036)

All time dummy coefficients are exponentiated. Number of observations = 846. Autocorrelation and heteroscedasticity consistent standard errors are in parentheses. The omitted reference year for the time dummy variables is 1993. *, **, and *** denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

The data on nominal personal health care spending are obtained from the Centers for Medicare and Medicaid Services (CMS). Crude death rate data are obtained from Center for Disease Control. National Consumer Price Index is obtained from the Bureau of Labor Statistics, *Economic Report of the President 2013.*

mortality reduction, numerous studies find that additional utilization of medical care may have no beneficial effect in the aggregate populations and even lead to higher mortality through medical error and injury. For example, Starfield (2000) estimates that roughly 225,000 deaths per year in the U.S. result from iatrogenic causes, which makes medical error and injury the third leading cause of death in the U.S. after heart

Table 3 Direct, indirect, and total effects on healthcare spending

Variable	Direct effect	Indirect effect	Total effect
Income	0.277*** (0.073)	−0.067** (0.031)	0.211*** (0.081)
Technology	0.417*** (0.058)	−0.116*** (0.001)	0.301*** (0.003)

Number of observations = 846. Autocorrelation and heteroscedasticity consistent SEs are in parentheses. Technology is the time dummy variable for year 2009. The omitted reference year for the time dummy variables is 1993. *, **, and *** denotes significance at the 0.10, 0.05, and 0.01 levels, respectively.

The data on nominal personal health care spending are obtained from the Centers for Medicare and Medicaid Services (CMS). Crude death rate and nominal personal income data are obtained from Center for Disease Control and U.S. Department of Commerce, Bureau of Economic Analysis respectively. National Consumer Price Index is obtained from the Bureau of Labor Statistics, *Economic Report of the President 2013.*

disease and cancer. More recent Dartmouth studies analyzing regional variations in medical practice patterns have concluded that more spending does not result in better health outcomes. Thornton (2011) estimates a health production function for the U.S. using state panel data and finds that once controls are included for technlogy, the estimate of the effect of medical care on health changes from positive to negative.

In order to check the results of our model for robustness, we conduct three additional regressions, including implementing a system GMM procedure with the original model, utilizing a two-step GMM procedure with the mortality rate for population over 44 years of age, and implementing a two-step GMM procedure controlling for the population under 45 years of age in the health equation. Except for income and technology estimates in the system GMM regression, which are close in magnitude to the original model estimates but not significant, the results for the key variables turn out to be reasonably close and statistically significant.

Discussion

The primary goal of our study is to analyze the effects of income and technology on the growth in healthcare spending while accounting for their effects on population health. Between 1993 and 2009, real personal healthcare spending per capita increased by 56.4 % from $4409 to $6896. During this same period, real per capita income increased by 23.1 % from $31,411 to $38,655. Given our total income elasticity estimate of spending of 0.211, we estimate that rising income increased spending by 4.9 % or $215 per capita. However, the increase in income over this period also produced better health resulting in an estimated decrease in the mortality rate of 2.5 %, and therefore 56,503 fewer deaths. If income had no effect on health, the rising level of income would have increased per capita spending by a somewhat larger 6.4 % or $282 per capita. As a result, the indirect effect of income on spending through health reduced per capita expenditures by $67, partially offsetting the higher spending induced by greater ability to pay for medical care. Our total income elasticity estimate of 0.211 is almost identical to the state-level panel data income elasticity of 0.21 to 0.22 obtained by Freeman (2012), but smaller than the country-level panel data estimate of 0.6 to 0.9 of Smith et al. (2009).[8] Our elasticity estimate of income with respect to mortality of −0.11 is about half as large as the state-level panel data estimate of Thornton (2011) of −0.24 for the period 1993 to 2000.

Our estimates suggest that advances in medical technology had a substantially larger impact than income on both spending and mortality during the period 1993 to 2009. The total elasticity estimate for technology of 0.301 implies that the introduction of new treatments and diagnostic tests increased real healthcare spending per capita by $1327, about six times as much as income, but simultaneously reduced the mortality rate by 19 % and saved 426,488 lives. The improvement in health from new medical technologies had the additional benefit of offsetting about 12 % of the cost or $512 per person. Our estimate of the contribution of technology to healthcare spending of 30 % is similar to Abrantes-Metz (2012) estimate of 32 %, and within the range estimated by Smith

[8] The objective of Freeman (2012) is to obtain an estimate of the income elasticity of healthcare spending, and therefore he includes few non-income factors.

et al. (2009) of 27–48 %. Using a similar approach, Di Matteo (2005) estimates that innovation contributed about 62 % of the spending increase for the period 1980–1998. However, his model includes only income and age distribution as explanatory variables, which likely biases up his estimate of innovation's contribution to spending.

While it is clear that increases in income and technology are important drivers of spending growth in the U.S., our estimates indicate that they are also associated with better population health, which may justify the cost associated with the higher level of medical expenditures. To assess the impact of medical innovation on social economic welfare, we need an estimate of both its cost and benefit. In our analysis, the cost of technology is the additional amount of spending contributed by innovation over the period 1993 to 2009. The benefit is the monetary value of lives saved from technological progress for that period. To estimate the economic value of lives saved, we use the Environmental Protection Agency's estimate of the value of a statistical life adjusted to year 2009 dollars of $7.85 million (Thornton and Rice 2008). Our calculation indicates that the net benefit of technological progress for the period 1993 to 2009 is about $3 trillion dollars. This suggests that technology, by affecting population health, produced benefits to society that substantially outweighed the cost. Since most economic value of life estimates range anywhere between $5 and $10 million, we also calculate the break-even economic value of life associated with technology. This is the monetary value of life for which the net benefit to society from technological advancements is zero. Our break-even estimate indicates that if the economic value of life is greater than $818,356 this would result in positive net social benefits, and therefore medical innovation that occurred over the period 1993 to 2009 would be worth it from a societal point of view. Since the majority of estimates of the economic value of life are well above the $5 million mark, this provides further evidence that the benefit of technology, in terms of the economic impact of lives saved, outweighed the cost.

We conduct a similar type of cost-benefit calculation for income. Cost is measured by the increase in healthcare spending that resulted from the increase in income per capita for the period 1993 to 2009. Benefit is measured by the monetary value of the decrease in mortality that resulted from rising income. Our estimate of the net benefit of income is $387 billion. Alternatively, our break-even estimate indicates that an economic value of life greater than $998,603 will produce benefits to society that outweigh the cost. This suggests that growth in medical care spending resulting from rising incomes during this 17-year period generated net benefits for society.[9]

Conclusions

A number of prior studies estimate the effect of income and technology on healthcare spending, but do not simultaneously take into account their effect on population health. We estimate that the net benefit of technological progress and rising per capita income for the period 1993 to 2009 is close to $3.4 trillion. We interpret this as an upper bound estimate since our time effects proxy for technology may capture other time dependent factors contributing to spending growth and improvements in health. Our estimate

[9] Because the measure of technology provides an upper bound, the calculated monetary benefit of technological advancement may be too high, while the monetary cost too low.

suggests that technology and rising incomes, by decreasing population mortality, produced benefits to society that outweighed the cost, and therefore policy initiatives to control costs by limiting new medical technologies may not be socially optimal. While such actions may contain rising spending, they may also militate against improvements in health that produce large social benefits. Our study suggests that future work on understanding healthcare spending growth should focus more on the pathways through which factors affect healthcare spending as well as potential benefits from improvements in population health.

APPENDIX

Variable Definitions and Data Sources [Mean, Standard Deviation]

Healthcare spending - real personal healthcare spending per capita, constant 2009 dollars. The data on nominal personal health care spending per capita by state of recipient are obtained from the Centers for Medicare and Medicaid Services (CMS) web-site http://cms.hhs.gov, and are estimates produced by the Office of the Actuary. National Consumer Price Index is obtained from the Bureau of Labor Statistics, *Economic Report of the President 2013* [5525.11, 1123.47].

Health/Mortality - crude death rate measured by number of deaths per 100,000 population. The data are taken from Centers for Disease Control website, http://wonder.cdc.gov [852.60, 128.05].

Income - real personal income per capita, constant 2009 dollars. Data on nominal personal income per capita are obtained from the Bureau of Economic Analysis, U.S. Department of Commerce website, http://www.bea.gov. National Consumer Price Index is obtained from the Bureau of Labor Statistics, *Economic Report of the President 2013* [35,398.78, 5763.43].

Education - percent of the state population 25 years of age or older with a high school degree or more. Data are taken from U.S. Census website, http://www.census.gov, annual March Current Population Report and American Community Survey [84.86, 4.49].

Unemployment - percent of the labor force unemployed. Bureau of Labor Statistics website, www.bls.gov [5.10, 1.54].

Insurance coverage - percent of the population with private or public health insurance. U.S. Census Bureau website, http://www.census.gov/hhes/www/hlthins [86.39, 3.98].

Medicare coverage - percent of the population with Medicare insurance. U.S. Census Bureau website,

http://www.census.gov/hhes/www/hlthins [13.78, 2.36].

Medicaid coverage - percent of the population with Medicaid insurance. U.S. Census Bureau website,

http://www.census.gov/hhes/www/hlthins [11.54, 3.52].

Non-HMO coverage - percent of the population not covered by an HMO health plan. It is measured as 100 minus the percent of the population covered by an HMO health plan. HMO data for years 1993–2005 are taken from various issues of *Health United States*; 2006–2008 are taken from *Statistical Abstract of the United*

States, 2012; 2009 are taken from the Kaiser Family Foundation website, http://kff.org. The original source of all data is Interstudy Publications, Competitive Edge reports [81.25, 12.31].

Physicians - number of physicians per 100,000 population. Excludes federal physicians and doctors of osteopathy (DOs). The data are taken from various issues of the *Statistical Abstract of the United States*. The original data source is the American Medical Association, Physician Characteristics and Distribution in the U.S. It reports non-federal physicians for years 1993–2002. Beginning in year 2003, it includes federal physicians. We adjust the data for 2003–2009 by an estimate of the number of federal physicians by state [236.47, 59.99].

Hospitals - number of beds in community hospitals per 1000 population. Data for years 1993 to 2000 are taken from various issues of the *Statistical Abstract of the United States*. Data for years 2001 to 2009 are taken from Kaiser Family Foundation website, http://kff.org. The original data source is the American Hospital Association Annual Survey [3.14, 0.99].

Alcohol consumption - alcohol consumption per capita age 16 years and older, gallons. National Institute on Alcohol Abuse and Alcoholism (NIAAA) website, http://www.niaaa.nih.gov, Surveillance Report #95 [2.29, 0.47].

Cigarette consumption - cigarette consumption per capita, packs. Data are taken from the Centers for Disease Control website, http://cdc.gov, State Tobacco Activities Tracking and Evaluation System. The original data source is the consulting firm Orzechowski and Walker [82.07, 29.34].

Obesity - percent of the population 18 years of age and older with a body mass index (BMI) of 30 or greater. Data for 1992–1994 are taken from the American Cancer Society website, www.cancer.org; 1995–2009 are taken from the Centers for Disease Control website, http://wonder.cdc.gov, Behavioral Risk Factor Surveillance System [20.75, 5.08].

Population density - population per square mile of land area. Data on land area are taken from U.S. Census Bureau, MAF/TIGER database. Population data are taken from Centers for Disease Control web-site, http://wonder.cdc.gov, and are U.S. Census Bureau and National Center for Health Statistics estimates of state populations [183.84, 250.17].

Elderly, Black, Hispanic, Female - percent of the population 65 years of age and older [12.66, 1.86], African-American [10.53, 9.54], Hispanic [8.10, 9.04], and Female [50.81, 0.78]. The data are taken from Centers for Disease Control web-site, http://wonder.cdc.gov, and are U.S. Census Bureau and National Center for Health Statistics estimates of state populations.

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