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ABSTRACT

Over 2009-2019 the seemingly inexorable rise in health care's share of GDP markedly slowed, both in the US and elsewhere. To address whether this slowdown represents a reduced steady-state growth rate or just a temporary pause we specify and estimate a decomposition of health care spending growth. The post-2009 slowdown was importantly influenced by four factors. Population aging increased health care's share of GDP, but three other factors more than offset the effect of aging: a temporary income effect stemming from the Great Recession; slowing relative medical price inflation; and a possibly longer lasting slowdown in the nature of technological change to increase the rate of cost-saving innovation. Looking forward, the post-2009 moderation in the role of technological change as a driver of growth, if sustained, implies a reduction of 0.8 percentage points in health care spending growth; a sizeable decline in the context of the 2.0 percentage point differential in growth between health care spending and GDP in the 1970 to 2019 period.

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1. INTRODUCTION

The decades-long rise in health care's share of GDP among developed economies slowed markedly from 2009 to 2019 (OECD 2021). The duration of this “bending of the curve” across a broad cross-section of OECD countries is novel relative to the observed data prior to 2009, although there were shorter pauses in the US and elsewhere in the 1970-2009 period (Figure 1).¹ The near ubiquity across industrialized countries of the 1970-2009 rising long-term trend and its post-2009 flattening suggests common causes. In this paper we seek to determine the quantitative importance of several causes and shed light on the question: Are we finally seeing a sustainable bending of the health care growth rate curve – or a just another temporary pause?

We consider five drivers of health care spending growth. The first is technological change. For decades science has continued to develop new treatments – most dramatically in the pandemic era with mRNA vaccines. On balance, these new treatments historically added to spending; a quarter century ago 81% of American health economists thought technological change was the main cause of health care spending growth (Fuchs 1996). Some technological change is exogenous, meaning it would be adopted within the current resource constraint, either because it reduces spending (assuming that any decrement in quality is sufficiently small that the net benefit remains positive) or that it has sufficiently high benefits relative to its cost to substitute for non-health-care goods and services. But other change, especially at the intensive margin², is endogenous and will only be adopted if willingness-to-pay is sufficiently high (Weisbrod 1991). The tension between the demand for costly medical innovations and the resulting budgetary pressures has led to widespread efforts to manage insurance coverage of and access to new technologies (OECD 2017).

In addition to technological change, we consider four other factors influencing health spending growth: 1) internationally correlated macroeconomic change; 2) population demographics; 3) health insurance generosity; and 4) unit prices of medical care goods and services.³ Although research findings differ about the magnitude of the elasticity of health care spending with respect to GDP, there is virtual unanimity that GDP is an important determinant of health care spending (Gerdtham and Jonsson 2000). Similar trends in population demographics among OECD countries are another driver of growth, especially the rising proportion of elderly, who consume disproportionate amounts of health care. Over time health insurance has become more generous, both with respect to services covered and out-of-pocket spending for a fixed bundle of services. Unit prices in medical care may rise faster than economy-wide inflation, possibly because productivity in service sectors may be systematically slower than the economy-wide average (Baumol 2012). On the other hand, prices are administered or negotiated in many

¹ The nomenclature of a “bending of the curve” became widespread at the time of the legislative debate on the Affordable Care Act. Here, the curve as defined as the time path of health consumption expenditures; a reduction in the growth rate implies a flatter health care spending curve as a share of GDP.

² Adoption of new technology has an impact that varies at both the extensive margin (timing of adoption) and the intensive margin (utilization of a new technology on a per capita basis) (Comin 2014).

³ An additional relevant factor is change in population health status over time, which we partially address within our adjustment for US demographic change described below. Comprehensive estimates of the contribution of health status changes to health care spending are confounded by endogeneity and measurement issues that are beyond the scope of this paper. Although improvements in population health status attributable to exogenous causes are a negative factor for demand for health care spending, changes in health status are rarely exogenous (COVID-19 is an obvious exception) because health status is itself a function of health care consumption.

countries, and may also respond to changes in income and/or higher cost, pointing to likely interaction effects among these factors, especially among income, new technology, prices, and the nature of insurance coverage.

In 2009 two of us published a paper (Smith et al. 2009) that quantified the relative importance of these five factors for US health care spending growth by borrowing an approach from Robert Solow's classic paper demonstrating the importance of technological change for overall economic growth (Solow 1957). Solow attributed the residual growth in GDP that could not be explained by growth in capital and labor inputs to technological change. Following in his footsteps, Smith et al. also treated technological change as a residual and found that both income growth and technological change were empirically important in explaining health care spending growth; income growth by itself explained 28-43% of the growth in US health care spending from 1960-2007, and its interaction with technological change explained another 13-27%. The remaining growth was attributed to the other three factors described above. In this paper we expand the scope of analysis to evaluate drivers of growth among OECD countries with available data – thus placing the drivers of growth in an international context. We also update and refine our earlier decomposition of health care spending growth for the US. Based on the conclusions of this broader OECD decomposition, which are largely consistent with results for the US, we evaluate the reasons for the post-2009 slowdown in the growth rate of health care spending. Our findings suggest that this flatter growth trend has roots stretching somewhat further back into the early 2000s and, looking forward, may continue to some degree.

Our current work is closely related to the existing extensive literature on the income elasticity of health care spending; growth in income remains a dominant explanatory factor for health care spending. However, our estimates of the sensitivity of health care spending in response to variation in economic growth vary in two ways from those in the literature. First, the literature is retrospective and concerned with estimating an elasticity parameter, whereas we primarily focus on implications for future health care spending. Second, we represent medical technology in a way that allows its effects to be projected as a function of macroeconomic assumptions.

2. DATA

Panel data for health care spending for 1970-2019 are available for 20 OECD countries.⁴ Because of differences in data availability, however, our analysis differs for the US and the other 19 OECD countries (hereafter OECD exUS). When analyzing OECD exUS data we define health care spending using the OECD's "Total Current Expenditures," which is closest to the definition of "Health Consumption Expenditures" in the US National Health Expenditure Accounts (Centers for Medicare and Medicaid Services 2021).⁵ We convert health care spending and GDP to constant dollars based on purchasing power parities from the OECD database and the US GDP deflator (Bureau of Economic Analysis 2020). We adjust the health

⁴ Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Iceland, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, United States.

⁵ The OECD series includes personal health care and administrative costs, and excludes government public health, investment and R&D spending. The National Health Expenditure Accounts definition of Health Consumption Expenditures differ slightly, however, in that it includes spending on government public health.

care spending data for known discontinuities and definitional inconsistencies based on OECD documentation.⁶

We define insurance coverage as the out-of-pocket share of spending on health consumption expenditures. Using the out-of-pocket share of spending as a measure of insurance coverage, while crude, is the best that can be done with existing data at the country level. Changes in the structure of insurance coverage (e.g., higher deductibles combined with a lower out-of-pocket maximum or changing coinsurance to copayment with no change in the average percentage paid out-of-pocket) and any accompanying interaction effects are not reflected in this measure of coverage and are therefore captured within the residual. For countries with missing data for out-of-pocket spending in earlier years, we extrapolate out-of-pocket share based on growth rates for the population-weighted average for other countries in the sample (excluding the US and South Korea, which are outliers).⁷ For the US we calculated the out-of-pocket share of health consumption expenditures from the US National Health Expenditure Accounts.

We estimate demographic effects for the US using an index of health care spending per capita by age, sex, and proximity to death or “time-to-death” cells, weighted by shares of population in those cells (The Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds 2021). This measure not only controls for the effects of population aging on health care spending but also captures the effects of changing mortality rates within each age cohort. Lower mortality rates change the concentration of medical care consumption within each age-sex cohort because the share of population at a given proximity to death is reduced, so average spending for the entire cohort is correspondingly lower. In other words, as mortality rates have improved over time, the distribution of population within an age cohort has shifted away from the relatively higher per capita health care spending experienced in the final months of life. This time-to-death adjustment reduces the contribution to health care spending growth that would otherwise be attributed to population aging. Because mortality rates are partially a function of health status, this adjustment also partially incorporates the effects of changes in population health status over time.

Data limitations require measurement of demographic effects for other OECD countries using a simplified version of the US index. Age cohorts are coarser, 0-18, 19-64, and 65+, and we cannot control for changes in time-to-death within cohorts. Furthermore, relative health care spending per capita by age cohort is only available for eight OECD countries in 2015 (Papanicolas et al. 2020). We therefore assume relative spending by age cohort is constant over time and that this distribution of spending by age is the same in the 11 other OECD countries for which no data on spending by age group are available. This latter assumption, however, is consistent with sensitivity tests for the eight countries with data; we find the implied contribution of demographic change to health care spending growth for those eight countries is not sensitive to calculating indexes based on own-country data versus the eight-country average.⁸

We have a measure of medical price inflation relative to economy-wide inflation (as measured by the chain-weighted GDP deflator) only for the United States, and even that measure

⁶ See Appendix, section 1 for detail on OECD data.

⁷ The sample of countries with complete data for out-of-pocket share extending over the entire sample interval is small (Australia, Germany, Denmark, Finland, France). However, results are not sensitive to this assumption as changes in insurance coverage based on this measure account for a very small share of health care spending growth.

⁸ See Appendix, section 2, for discussion.

is pieced together from different sources over time. For the US from 1996 forward we use the National Health Expenditure Accounts chain-weighted deflator for personal health care (Centers for Medicare & Medicaid Services 2020). The 1990s saw the introduction of a Producer Price Index (PPI) for health care, which was complete by 1996 and marked a substantial improvement over the previously available Consumer Price Index (CPI). Unfortunately the CPI is seriously flawed as a measure of sector-wide medical prices (Berndt et al 2000, 2001; Catron and Murphy 1996).

Rather than rely on the CPI for the 1970-1995 period, we impute medical price growth based on three determinants of medical price inflation: input price inflation; total factor productivity (TFP) growth; and producer profit. Input price inflation for health care is based on estimates from the Bureau of Labor Statistics (BLS) Office of Productivity and Technology from 1987-1995 and on Center for Medicare and Medicaid Services (CMS) estimates of input price inflation for 1970-1987 (Ho and Samuels 2006, Appendix B).⁹ Accurate estimates of medical care TFP require reliable measures of output price to enable the measurement of growth in real terms (quantity), so estimates of TFP for the 1970-1995 period reflect the flaws in the medical price data.¹⁰ Rather than rely on these estimates we assume upper and lower bounds on long-term growth in medical care TFP as we discuss further below. We also lack data on profit margins. We assume no long-term change in profit margins; over decades the effect of any changes in margins is likely small relative to changes in other factors.

Measures of medical prices are not available on a consistent basis for the OECD exUS sample. Several of these countries do not reimburse on a fee-for-service basis, making measurement of growth in unit prices problematic. In our main analysis we therefore omit this factor from the decomposition of growth for these countries. In the absence of relative price data, we incorporate a proxy for variation in medical price inflation across countries based on the Baumol cost disease model, relative labor compensation per hour worked and GDP per hour worked (US dollars, PPP, OECD 2021). We discuss the details of this proxy below.

3. METHODOLOGY

Decomposition of Factors Contributing to Growth

Our decomposition of growth in US health care spending is summarized in Equation 1.1, which we estimate using US data, and for the OECD exUS in Equation 1.2, which we estimate using OECD data. The two equations differ mainly in the inclusion of the relative price term P in the US equation. These identities parallel Solow's decomposition of economy-wide growth (Solow 1957); we account for major factors contributing to growth other than technological change and, like Solow, attribute the residual to technological change. Because the residual includes all factors that are unaccounted for, however, this implicitly assumes technological change is the dominant omitted factor. We allow lagged effects of income; we estimate the lag structure to be a lagged five-year moving average.

⁹ See Appendix, section 3, for detail on data sources and methodology for the estimation of input price inflation.

¹⁰ Estimates of growth in TFP for medical services for the pre-1996 period are consistently negative, implying persistent long-term declines in productivity which does not seem plausible and likely reflects upward bias in output price measures.

$$(1.1) \ln(H_{USA,2019}/H_{USA,1970})/N = \varepsilon_y \ln(\text{MA}(Y_{USA,2019}, 5)/\text{MA}(Y_{USA,1970}, 5))/N + \varepsilon_i \ln(I_{USA,2019}/I_{USA,1970})/N \\ + (1 + \varepsilon_p) \ln(P_{USA,2019}/P_{1970})/N + \ln(D_{TTD,USA,2019}/D_{TTD,USA,1970})/N + \epsilon_{USA,2019,1970}$$

$$(1.2) \ln(H_{C,2019}/H_{C,1970})/N = \varepsilon_y \ln(\text{MA}(Y_{C,2019}, 5)/\text{MA}(Y_{C,1970}, 5))/N + \varepsilon_i \ln(I_{C,2019}/I_{C,1970})/N \\ + \ln(D_{C,2019}/D_{UC,1970})/N + \epsilon_{C,2019,1970}$$

$H_{USA,yr}$	=	US constant-dollar health consumption expenditures per capita, yr= year
$H_{C,yr}$	=	constant-dollar total current expenditures per capita, country c, year=yr
$\ln(\text{MA}(Y_{USA,yr}, 5))$	=	moving average of $\ln(\text{real US GDP per capita})$, 0 to 5 years
$\ln(\text{MA}(Y_{C,yr}, 5))$	=	moving average of $\ln(\text{real GDP per capita, country c})$, 0 to 5 years
$I_{C,yr}$	=	out-of-pocket share of health care spending measure, country c
$P_{USA,yr}$	=	US relative medical price
$D_{TTD,USA,yr}$	=	US index of demographic contribution to health care spending (age-sex-time-to-death)
$D_{C,yr}$	=	index of demographic contribution to health care spending (age-sex)
$\epsilon_{C,yr i,yr j}$	=	residual contribution to growth from year i to year j
c	=	country
yr	=	year
N	=	number of years

The ε parameters are the elasticities of constant dollar per capita health care spending with respect to each explanatory factor. We do not estimate the elasticity for the demographic index because by definition it equals 1.0.

Based on our definition of insurance coverage, changes in coverage are effectively treated as a price change, with the price to consumers based on average out-of-pocket share. We therefore assume ε_i and ε_p can be treated as price elasticities, and fix the value of these elasticities using the Rand Health Insurance Experiment estimate of -0.1 (Manning et al 1987, Table 9, which uses average coinsurance rates). As noted above, this measure of average insurance coverage does not capture incentive effects that occur at the margin (if the marginal price differs from the average price) or non-pecuniary constraints on coverage that may alter incentives for developing or using new medical technology. The estimated contribution from the residual will therefore reflect any interaction effects between technology and insurance coverage that occur at the margin, as well as other variation in insurance coverage. Such an interaction effect is potentially important in magnitude because constraints on coverage may be specifically targeted to constrain access to newly available technologies, influencing rates of adoption and diffusion and therefore spending. We assume the effects of technological change dominate the residual for health care spending growth but that the residual also incorporates effects from the structure of insurance coverage that will shape the interpretation of results.

Estimating the income elasticity and income-technology interaction effect

We define medical technology as the feasible set of treatment options and organization of care delivery and assume that it is common across our sample of countries over time. As a result, year fixed effects capture shared variation across countries over time in this set after controlling for other factors. We therefore use year fixed effects as a proxy for changes in medical technology over time.¹¹ We also include country fixed effects to capture country-specific institutional characteristics that remain constant over time. We then estimate income elasticities with and without year fixed effects (Equations 2.1 and 2.2). Based on the Omitted Variable Theorem – and noting that the main effect of technology is controlled for by the year fixed effects in equation 2.1 whereas it is included in the residual of equation 2.2 – we define the difference in the coefficients on income between the two specifications, $\beta'_y - \beta_y$, as an estimate of the coefficient on the interaction effect between aggregate income and technology. We term the coefficient on income in Equation 2.2 the “expenditures elasticity.”

$$(2.1) \quad \ln(H_t) - \beta_I \ln(I_t) - D_t = \alpha + \beta_y \text{MA}(\ln(Y_t), 5) + \sum_{c=0}^I c_i + \sum_{t=0}^T yr_t + \mu_{it}$$

$$(2.2) \quad \ln(H_t) - \beta_I \ln(I_t) - D_t = \alpha + \beta'_y \text{MA}(\ln(Y_t), 5) + \sum_{c=0}^I c_i + \mu_{it}$$

H_t	= real per capita spending on health consumption, time t
I_t	= out-of-pocket share of health care spending, time t
D_t	= demographic index, time t
Y_t	= real per capita GDP, time t
c_i	= fixed effects for each country i
yr_t	= fixed effects for each year t
$\text{MA}(\ln(Y_t), 5)$	= moving average of $\ln(Y_t)$, 0 to 5 years

Equation 2.1 parallels a relatively standard approach for estimating income elasticities (although non-income variables differ). The inclusion of 2-way fixed effects in this model implicitly treats variation captured by these effects as exogenous.¹² But estimated year fixed

¹¹ Assuming new technology is introduced everywhere simultaneously is a strong assumption. It can be somewhat relaxed to assume that the country-specific lag structure in technology introduction is stable and that the rate of new technology introduction is stable.

¹² The recent econometrics literature cautions against the use of two-way-fixed effects models to estimate a causal program or treatment effect because of possible omitted variables that are correlated with the identifying variation, often in the context of a difference-in-difference model (Chaisemartin and d’Haultfoeuille 2018, 2020; Roth, et al., 2022; Sun and Shapiro, 2022). We, however, are not trying to estimate a causal treatment effect but rather decompose variation in spending into its components and in particular to discriminate the contribution of exogenous and endogenous technology under the assumption that year fixed effects represent a shared contribution of technology across countries. Our interpretation, however, does rely on the assumption of no omitted exogenous variable other than technology that would be more than negligibly correlated with year fixed effects across countries over a five- decade period; as we discuss below, we cannot think of such a variable. For these purposes we treat health status changes as endogenous; thus, our estimates are in the spirit of a reduced form equation.

effects tend to be strongly correlated with variation in real per capita GDP. Based on our assumption that shared variation over time acts as a proxy for the change in medical technology, this correlation implies an interaction effect between income and technology. Importantly, the ability to estimate this interaction means that this effect can be projected forward as a function of economic growth, which allows one to evaluate implications of the projected future macroeconomy for future health care spending growth. We interpret the difference in coefficients between Equation 2.1 and 2.2 as an estimate of the coefficient of an interaction effect between medical technology and income growth. Since the menu of options for medical treatment is assumed to be the same across countries, this interaction effect can be expected to capture variation in the rates of adoption and diffusion for new medical technologies (and therefore spending) as demand for access to these technologies varies as a function of income at the level of the within-country insurance pool(s).

With panel data across countries and periods, individual countries in the sample may well have serially correlated errors.¹³ We therefore estimate robust standard errors clustered on country (adjusted for degrees of freedom) for the coefficients of equations 2.1 and 2.2 (White 1980, Davidson and MacKinnon 1985).

As noted above, we estimate the lag structure in the transmission of macro income effects to health care spending that best fits the entire OECD sample. While health care spending is procyclical, it responds to business-cycle fluctuations with a lag (Centers for Medicare & Medicaid Services 2022). We estimate the lag structure of the relationship between H_t and Y_t as a moving average over a period from the 5th preceding year to the current one.¹⁴

The prevalence of third-party payment buffers household demand for medical care from the immediate effect of macroeconomic shocks. Instead, the response of the health sector spending to changes in the macroeconomy operates mainly through the delayed actions of intermediaries such as employers, governments, insurers, and providers, who act as agents for consumers, making decisions that influence the composition of medical treatment. The nature of this response is filtered through contractual arrangements, laws and regulations that change gradually over time. In effect, this lag describes the results of endogenous institutional change that occurs as a function of income changes, and involves lags in transmission through multiple channels of decision making. Although the lag in the income effect does not strongly influence the decomposition of growth over decades, it is important to the interpretation of growth in the health sector near cyclical inflection points. This is especially relevant to the post-2009 period, which immediately followed the Great Recession.

As noted above, OECD data lack information on relative medical price, and this omission may bias the income coefficients in the estimation of equations 2.1 and 2.2. While relative medical price cannot be measured explicitly in the OECD data, it is possible to define a proxy for this variable based on the predictions of the Baumol cost disease model. That model predicts relative medical price will vary as a function of the differential between economy-wide wage growth and labor productivity growth because health care providers must offer competitive wages that are determined by labor productivity in progressive sectors (Hartwig (2008), Bates

¹³ Error terms for adjacent or nearby countries may also be correlated, but trying to adjust for such correlations is problematic given the small numbers of clusters so we have not also clustered on year. As a result, our standard errors may be biased down (Cameron, et al. 2008).

¹⁴ See Appendix, section 4 for detail on the estimation of the lag structure for the income variable.

and Santerre (2013), Lorenzoni et al (2019)). Thus, the model predicts unit costs for health care (c_h) will increase over time as a function of real wages relative to productivity growth in the progressive sector, and those increases will feed through to medical price inflation. The ‘Baumol variable,’ or $\ln(w/y)$, can be defined for a large subsample of the OECD pooled sample used for estimating income and expenditures elasticities.

$$(3) \quad \ln(c_h) = \lambda \ln(w/y)$$

c_h = unit costs of production, health care sector
 w = real compensation per employed person (economy-wide)
 y = real GDP per employed person (economy-wide)

Based on the subsample of 14 countries where $\ln(w/y)$ can be measured, we can estimate the interaction effect between income and relative medical price by adding this variable to the model specification in equations 2.1 and 2.2.¹⁵ If there is an interaction effect between income and relative medical price, we would expect the coefficient on real per capita GDP to change when this proxy is included in the model. The interaction effect between income and relative price is defined as the difference in the coefficients of real per capita GDP when the Baumol variable is included or excluded. We assume this interaction effect applies for the OECD sample as a whole (i.e. the 20-country versus the 14-country sample used for estimation), and adjust income and expenditures elasticities to exclude this effect.

4. RESULTS

The results of estimating Equations 2.1 and 2.2 are shown in Step 1 of Table 1. The expenditures elasticity of income, β'_y , which incorporates the interaction between time period effects and income in the coefficient, is 1.338, is substantially higher than the estimate of 0.885 for β_y , which controls for the main effect of technology by including year fixed effects.

As discussed above, we can adjust income and expenditures elasticities to account for the estimated interaction effect between income and relative medical price estimated based on the Baumol variable (relative economy-wide real wage/labor productivity). The results of estimating the model with and without the Baumol variable for a subset of the OECD data (14 countries, 1990 to 2019) are also shown in Step 2 of Table 1, along with the implied adjustments to income and expenditures elasticities. As predicted, the coefficient on this variable is positive and significant. Its inclusion reduces the coefficient on real per capita GDP, implying a positive interaction effect between the income variable and relative medical price, although the implied interaction effect is small for Equation 2.2 (which excludes period FE’s). This difference in the income coefficients implies that in the absence of the proxy for price in the regression the income and expenditure elasticities capture variation that should be attributed to relative price effects. The range of values for the income and expenditures elasticities are defined by the

¹⁵ See Appendix, section 6, for data definitions and model equations. The 14 countries are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Japan, Netherlands, Norway, Portugal, Spain, United Kingdom, and the United States.

inclusion/exclusion of the estimated interaction effect and are shown in Step 3 of Table 1; the high end of the range assumes zero interaction between income and relative medical price.

The results of the decomposition of growth in real per capita health care spending for the United States and the comparison of a simplified decomposition for the both the US and the OECD exUS sample are shown in Table 2 for the entire 1970 to 2019 period as well as for the 2009 to 2019 period, the decade of lower growth in the health care share of GDP shown in Figure 1. The results shown in Table 2 include both estimated ranges and midpoints for the various drivers of growth in health care spending; our discussion focuses on the midpoint of those ranges.

Over the entire 1970-2019 period the drivers of growth in health care spending for the US and the OECD exUS are broadly similar; income and medical technology are the dominant factors in both cases, with insurance and demographics playing much smaller roles. For the US the role of relative medical price inflation is a relatively minor factor. There are, however, some notable differences between the US and the OECD exUS results; income plays a more substantial role for the OECD exUS, accounting for a little over half of the growth in the OECD exUS sample, while explaining less than 40 percent of growth for the US. The expansion of insurance coverage plays a smaller role in the OECD exUS sample than in the US, in part reflecting a lower starting point for out-of-pocket share of health spending and hence less change.

The results of the decomposition for the US over the entire 1970-2019 period are broadly similar to results from Smith et al. (2009) for the 1960-2007 period. Income has a slightly higher role at the midpoint (39.0% versus 35.9%) than in the earlier results as does technology (38.3% versus 34.2%). Not surprisingly demographic change is now more important with recent acceleration of population aging (8.5% versus 7.2%); in fact, that comparison understates the increase in the demographic effect because of the change in methodology in these later results to account for shifts in composition by proximity to death. Other notable differences in the decomposition are the smaller estimated contribution from relative medical price (7.9% versus 11.9%) due to a recent deceleration in relative medical price growth combined with changes in methodology,¹⁶ and a smaller role for insurance coverage (6.2% versus 10.8%).

The residual in the 1970-2019 simplified decomposition for all OECD countries in Table 2, which includes the effects of both technology and medical price inflation, is an order of magnitude smaller contributing factor for the OECD exUS countries than for the US (2.4% versus 23.5%). To place this result in context, even if the contribution to growth from relative medical price inflation is assumed to be zero for the OECD exUS, which would make the residuals on lines g and h equal for the OECD exUS, the residual attributed to technology for the US would still be substantially larger. In other words, by this measure exogenous medical technology has been a relatively more important driver of health care spending growth in the US.

The lower panel of Table 2, which narrows the time frame to the 2009-2019 decade, shows a markedly different decomposition of growth than one sees over the entire 1970-2019 period. Three differences are notable. First, the contribution from demographics rises substantially in importance (accounting for almost thirty percent of growth for the US and over a third for the OECD exUS), reflecting a combination of higher contribution to growth from the

¹⁶ The estimates in this paper splice growth in the CMS price deflator for personal health care for the period of PPI availability; the estimates in Smith, et al. (2009) used an imputation for price over the entire period.

aging of the postwar baby boom cohort (an acceleration of a trend that begins in the late 1990s), and slower growth in health care spending due to other factors. Second, the effect of relative medical price inflation in the US turns from a net positive to a negative, implying that in this decade medical prices grew more slowly than economy-wide prices. Finally, relative to the earlier period the contribution to growth from the technology residual falls sharply for both the US and for the OECD exUS.

An additional factor relevant to the flatter post-2009 trend for health share of GDP is less obvious from the table, namely the lagged effect of income on health care spending following the severe global recession accompanying the 2008-2009 financial crisis. The initial insulation of the health sector from the effects of recession resulted in an increase in health share of GDP during the recession, followed by an extended period of slower growth from the delayed effects of the recession on health care spending. The contribution of income to growth post-2009 is close to its average for 1970-2009, which means this factor accounts for close to a proportional share of the recent slowdown in growth. This close to proportional contribution to slower growth occurred despite the acceleration of economic growth over this period, reflecting the negative impact on health care spending growth from the 2008-09 recession, which extended through about 2014. This lagged impact occurs through both the direct income effect and through the income-technology interaction effect, which is also a lagged function of real per capita GDP.

From this analysis we conclude that the bending of the curve for health care spending for both the US and OECD exUS from 2009-2019 shown in Figure 1 is due to a combination of the lagged effects of the 2008-2009 recession and the declining residual, partially offset by the substantial positive effect of population aging. For the US an additional contributing factor to slower post-2009 health spending growth is the negative contribution from relative medical price inflation.

5. IMPLICATIONS OF THE POST-2009 PERIOD FOR FUTURE HEALTH CARE SPENDING GROWTH

What implications does the historical decomposition have for the sustainability of the slower post-2009 health care spending growth – after the effects of the Covid-19 pandemic have subsided? The answer, of course, requires predicting the future course of the main factors affecting health care spending. Over the 2009-2019 decade demographics contributed positively to growth, but three other factors combined to slow growth: the lagged effect of the 2008-2009 recession; a smaller implied contribution from the technology residual; and in the US lower relative medical price inflation. As we describe next, the positive effect of demographic change is likely to continue in the near term. The future effects of the three negative factors are likely to differ; the effects from income and relative price are probably temporary in nature, but the reduced contribution to growth from the exogenous technology effect could exert sustained downward pressure on future health spending growth. We assume changes in insurance generosity will play a positive but minor role as the decline in out-of-pocket share continues the levelling out that is observable in the historical data and do not discuss its role further.

Demographic change

The contribution to health care spending attributable to population aging is reasonably predictable given birth rates, mortality rates, net immigration rates, and variation in relative

health care spending per capita by age (assumed constant). Variation in the effect of demographics, both over history and in the future, is dominated by a wave effect resulting from the aging of the post-WWII generation into age cohorts requiring more intensive medical care. Based on demographic indexes for the US population, we are about five to ten years past the peak demographic contribution to health care spending growth associated with this wave (The Boards of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds 2021). Nonetheless, the contribution to health care spending growth from population aging is likely to remain well above the historical mean for the next twenty years before tapering off and subsiding to a trend contribution that is comparable to experience prior to the beginnings of this demographic wave in the late 1990s. Historical patterns in demographic indexes estimated for OECD countries exhibit a similar recent acceleration, and given the broad correlation across OECD countries in the aging of the post-WWII generation, one can expect to see a sustained higher contribution to health care spending growth from demographic change (Lorenzoni et al 2019), followed by an eventual tapering of this contribution.

Income

As noted above, the contribution to slower growth from the income effect after 2009 reflects the extended effects of the Great Recession. Given the 5-year moving average lag incorporated in our model, this lagged effect of the Recession extended through 2014, with no lasting implications from income effects for the long-term future trajectory of health care share of GDP.

Relative medical price inflation

The post-2009 negative contribution to US growth from relative medical price inflation contrasts with its consistent positive contribution through the prior four decades. The long-term implications can be explored by evaluating the drivers of this sustained slowdown and their pattern over time. Short-term variation in medical prices reflects a complex mix of factors including increasing provider consolidation (Gaynor et al. 2015) and shifts in payer mix, which can affect relative price inflation in the short-term because Medicare and Medicaid pay substantially lower prices than commercial payers (Kollar and Khullar 2019). In particular, the Affordable Care Act's reduction in Medicare reimbursement, particularly for hospitals, may have contributed to slower medical price growth in the 2009-2019 period. Nonetheless, while changes in institutions and policy may influence prices temporarily and with differential effects for individual payers, the long-term trend across all payers must necessarily track underlying growth in the unit costs of treatment. Those unit costs are driven by input price inflation, relative growth in medical care productivity (Total Factor Productivity or "TFP"), and changes in producer margins, which we assume have a small net contribution to growth over the long-term, because we consider continuous margin expansion or compression unrealistic. This relationship between price inflation and its determinants is captured in the price dual representation of the equation for total factor productivity, which represents relative output price inflation as the sum of input price inflation minus growth in total factor productivity (Jorgenson and Stiroh 2000).¹⁷

¹⁷ The 'price dual' representation of the equation for total factor productivity is a transformation of the standard form of the decomposition of output growth for the estimation of TFP (e.g. all variables in real terms) to a relationship in terms of price growth: growth in relative output price inflation is equal to the sum of contributions from factor input price inflation (by capital, labor, and three intermediate inputs: energy; materials; and services, or KLEMS) minus growth in TFP. These measures do not adjust for changes in quality from new goods, a standard problem with price

This long-term relationship between output and input price inflation can be most easily observed by considering relative price indexes in terms of levels over time (the relationship in terms of growth rates is somewhat obscured by volatility). In evaluating this relationship, we focus on the period from 1996 forward when producer price indexes are available for major US health sectors. We exclude data from 2020 forward due to the temporary (we hope!) distortions associated with the effects of the COVID pandemic. Index values for relative medical price and relative input price (both relative to economy-wide price inflation as measured by the chain-weighted GDP deflator) are shown in Figure 2 (a straight line roughly approximates a constant growth rate).¹⁸ The marked flattening in slope for both relative medical price and relative input price that we see in Figure 2 implies a sustained reduction in the growth rate for both relative output and input prices with similar timing – from about 2010 forwards (from 2009 for input prices).

A decomposition of medical price inflation can illuminate the contributions to growth from input price inflation compared with growth in total factor productivity. Such a comparison is useful because the long-term implications of slower price inflation from surging productivity differ from those of a deceleration driven by input prices. William Baumol hypothesized that the key driver of rising relative price inflation for service industries – particularly where services are highly customized as is the case here – is the inherent difficulty in improving productivity (Baumol 2012). Thus a critical question for the long-term is the extent to which the recent slowing trend in medical prices is associated with lower input price inflation or faster productivity growth. A sustained improvement in productivity growth would suggest the possibility of structural change within the health sector that could reasonably be extrapolated forward.

We can further break down the contributions to input price inflation from individual factor inputs, to see if a particular cause for the change in trend stands out. BLS estimates of total factor productivity are based on a decomposition of growth in the quantity of output as a function of the sum of contributions from each factor input to production (KLEMS) plus TFP. Transforming this basic equation for the decomposition of growth into a parallel equation in terms of price growth allows one to decompose the contributions to relative medical price inflation. The contribution to output price growth from factor input prices is equal to its factor share times input price inflation for that factor; the residual unexplained growth is attributed to growth in TFP. We use time-series data for output price, factor shares, factor price indexes, and estimated TFP from the BLS Office of Technology and Productivity for this purpose. The resulting decomposition illustrates the contributions to relative medical price inflation growth from input prices (broken out by capital, labor and intermediate inputs) and productivity growth.

The results of this decomposition are shown in Table 3. The slower growth in relative medical prices from 2010 forward proves to be primarily due to similar trends in input prices (as

indexes. To the degree quality has improved, our measure overstates the contribution of relative price inflation to spending.

¹⁸ The index values closely approximate the trend in the log of the indexes; a straight line for the log of the index implies a constant growth rate. For this period of time, the difference in trend between the level and log is small.

suggested by similar trends in the comparison in Figure 2) rather than medical care TFP.¹⁹ Disaggregating among input prices, the slower growth in input price inflation after 2010 reflects contributions from all three categories of factor inputs (capital, labor, and intermediate inputs). However, capital price inflation shows the sharpest deceleration in the post-2010 period, accounting for close to half of the deceleration in growth, well above its 16.4 percent share of total factor inputs in 2010. This negative trend in capital input prices was concentrated in hospitals and long-term care facilities (not shown), which exhibited rapid growth in the relative price of capital from about 2002 through 2009, followed by negative growth from 2010 forward. In contrast, the post-2010 slowdown in the prices of labor and intermediate inputs was more muted in magnitude, but their impact on output price is magnified by their relatively large share of costs (36.5 percent for labor and 47.1 percent for intermediate inputs in 2010). There is a minor increase in the estimated contribution from TFP (from -0.2 to -0.1). On balance, the change in trend for input price inflation is the dominant explanatory factor behind the slowdown in relative output price inflation for the period from 2010 to 2019.

What does this result imply for the sustainability of the post-2009 slowdown in medical price inflation? Although for the 2009-2019 period, the prices of inputs in the production of health care grew more slowly than economy-wide input prices, competition for factor inputs across industry sectors limits any long-term divergence in health care factor prices from economy-wide factor input prices. In other words, over the long-term, changes in health care input prices can be expected to grow at a similar pace as economy-wide input prices. As a result, the largely input price-driven nature of the recent slowdown in US medical price inflation suggests that this change in trend is not likely to persist over the long-term.

Technology residual

The final – and arguably most interesting – major factor contributing to slower health care spending growth for the post-2009 period is the sharp decline in the residual found in both the US and the OECD exUS decompositions. This residual includes the effects of highly beneficial new technologies that would have been adopted even if income were constant, as well as new cost-reducing technologies that have little if any detrimental effect on quality. Technology for these purposes could include changes in the nature of treatments for disease or in the organization of care delivery. The decline in the residual suggests that the cost-reducing type of innovation may have become more prominent relative to highly beneficial but expensive treatments. A reduction in expenditure trend attributable to exogenous technology is consistent with Bloom, et al.'s finding that the cost of finding new ideas to reduce cancer and heart disease mortality is rising – suggesting diminishing returns to medical research in the development of promising new technologies (Bloom et al 2020). Additionally, as the health care sector's share of GDP has expanded, the opportunity cost threshold for adopting an innovation within the current budget constraint has risen, implying decreased adoptions and/or greater constraints on diffusion. More generally, this interpretation of a change in the nature of innovation is consistent

¹⁹ It should be noted that the deceleration in the CMS price index for personal health care from 2010 is somewhat greater than that for the BLS measure of output price inflation from the TFP accounts (deceleration of -1.3% versus -0.8).

with the literature on induced innovation (Acemoglu and Linn 2004, Agha et al. 2022, Blume-Kohout and Sood 2014, Finkelstein 2004).

An alternative perspective on the nature of changes in medical technology and its relationship to slower growth that is consistent with the hypothesis of a shift towards the development of cost-saving medical technologies is suggested by a micro analysis of trends in health spending tracked by medical condition (Cutler et al. 2019), who find that the trajectory for growth in health care spending varies systematically by medical condition. In particular Cutler, et al. find a substantially slower growth path for cardiovascular and cerebrovascular disease – areas where preventive technologies have proven successful in reducing the rate of adverse health events requiring expensive treatment episodes. That said, their estimates leave a large share of slower growth unexplained. More importantly for our purpose of interpreting the fall in the residual, changes in health status seem unlikely to exhibit a one-time structural break such as that we discuss below – a gradual trend in health status seems more consistent with evolving patterns of treatment that would be expected to occur in practice.

As we have already noted, the residual reflects the effects of any variable omitted from our estimation. As also discussed earlier, the channel for imposing constraints on adoption and diffusion of new technologies may well function through changes in the scope and restrictions of insurance coverage that are not captured by our insurance proxy and are therefore included within the contribution from the residual. Based solely on the trend in the spending residual, it is not possible to distinguish between the effects of a fundamental shift in the nature of medical innovation itself and a more limited alternative of a shift towards increasingly active management of insurance coverage with an eye towards cost-benefit assessment.

Unlike the US residual, interpreting the decline in the OECD exUS residual is complicated by its inclusion of both technology and medical price effects. As already noted, however, the magnitude of its decline is much steeper than that of the US residual. Thus, assuming the magnitude of any post-2009 decline in the contribution to growth from the medical price component for the OECD exUS is similar to the US, the decline in the OECD exUS residual attributable to technology would remain considerably larger than that observed for the US.

The common decline in the residual in both the US and the cross-country OECD exUS samples supports attributing this effect to a shared change in the exogenous trend attributable to medical technology that applies to all countries. Beyond the globally correlated effects of the global recession and demographic effects, which are already controlled for in our results, technology appears to be the only remaining factor broadly shared across all these countries that could plausibly account for this common decline. The common trend in exogenous technological change suggests the possibility of a structural break in the contribution to healthcare spending growth from advances in and changes in the nature of medical technology. We therefore test for the presence of a structural break in the time-series for the simplified residual for both the US and OECD exUS.

Since the timing of a possible structural break is uncertain, we use the Quandt-Andrews test for a single breakpoint in 1970-2019 sample.²⁰ To implement this test we use a smoothed time series for the contribution from the residual (three-year centered moving average) to reduce

²⁰ See Appendix, section 7 for further detail and for test results for structural break in residual.

volatility. The null hypothesis of no structural break is rejected at the 1% level for both the US and the OECD exUS; the Quandt Likelihood Ratio statistics are 20.58 for the US and 29.59 for OECD exUS (Hansen 1997). The most likely breakpoint date identified by the test is 2004 for the OECD exUS and for 2005 for the US, which suggests that the bending of the health care share of GDP shown in Figure 1 has roots that extend somewhat further back than 2009.

The annual contributions to growth in health care spending from the combined technology and medical price residual for the United States and the OECD exUS are shown in Figure 3, along with the mean contribution to growth from the residual before and after the structural breaks. Although these breakpoints predate the 2009 split used in our decompositions, which we selected based on the pattern in the health share of GDP shown in Figure 1, the implied contribution to growth is consistent with the substantially lower average contribution for that overlapping period.

Not only is the timing for the break similar between the US and the OECD exUS, but the size of the reduction in the mean contribution to growth from the residual after the breakpoint is also reasonably similar for both, -1.5 and -1.1 percentage points for United States and OECD exUS, respectively. (Figure 3). For both the US and the OECD exUS the changes in contribution from the residual are also consistently sustained over the roughly fifteen years after the identified structural break, cycling around the post-breakpoint mean. A likely proximate cause for this structural break was the fiscal strain on health care budgets from the sharp upturn in health share of GDP during the global recession of the early 2000s following the stock market crash with the bursting of the technology bubble.

To allow an apples-to-apples comparison of the US and OECD exUS decompositions, the values for the simplified residual just discussed include relative medical price effects. However, for the US the data permit the estimation of a residual that excludes relative price effects. This residual can be attributed more confidently to the effects of exogenous technological change, allowing a more precise estimate of the contribution of technology before and after the structural break. At the midpoint of the decomposition the post-2004 contribution of the residual, the growth rate of real per capita health care spending as a share of GDP is reduced 0.8 percentage points. For context, this reduction occurs in the context of a differential between the growth rate of US personal health care spending and the growth rate of GDP of 2.0 percentage points for 1970 to 2019.

Any interpretation of the residual depends on the comprehensiveness with which we can control for factors contributing to variation in health care spending as well as the magnitude of measurement error. Our attribution of the break in the residual to exogenous technological change is supported by the consistency of the shift in its mean contribution to growth after the break both in timing and magnitude. In contrast, a sharp and isolated decline captured in the average for the longer period would be more indicative of an event-driven, non-recurring impact. The consistency of the shift in the mean contribution over time is implied by the test for structural change and can be observed in Figure 3. Our attribution is further supported by its breadth across individual countries in the OECD sample, to which we now turn.

Country and regional patterns in the residual

Effects on spending driven by country-specific policy initiatives or country-specific relative medical prices will generate more idiosyncratic effects by country and region than one

would expect from the effects of a shared change in the nature of medical technology. Changes in health policy or in insurance coverage via incentives to providers will not be coordinated in lockstep around the world; rather, we could expect to see a pattern of individual countries with relatively large effects, or possibly regional clusters, in cases where neighboring countries tend to coordinate policy initiatives. A pattern of a broad slowdown across most countries in the sample is most consistent with a change in the nature of technology, whereas changes in the structure of insurance coverage for individual countries in the sample – or in relative medical price – are more likely to generate a pattern where the reduction in trend is disproportionately accounted for by a small number of countries or possibly concentrated regionally.²¹

To determine the breadth of the slowdown, we estimated a pooled regression analysis of the pattern across countries in the OECD residual after the identified structural break. Regression specifications to estimate the pattern of effects across countries are shown in Equation 4.1 and 4.2. The dependent variable is the technology residual using a centered 3-year moving average to smooth volatility. Equation 4.1 is a pooled regression that estimates the reduction in the contribution to health care spending growth from the residual on average across the 20 OECD countries in the sample after the structural break identified in 2004. Equation 4.2 estimates the post-structural break change in trend on a country specific basis. Again we estimate with cluster-robust standard errors by period.

$$(4.1) \quad \text{MA}(\epsilon_{c,t}(I), 3) = \alpha + D2004_t + \sum_{c=0}^I c_c + \mu_{it}$$

$$(4.2) \quad \text{MA}(\epsilon_{c,t}(I), 3) = \alpha + D2004_t c_c + \sum_{c=0}^I c_c + \mu_{it}$$

MA($\epsilon_{c,t}(I), 3$) = residual, centered 3-year moving-average
 c_c = fixed effect, country c
D2004_t = 1 for year ≥ 2004
= 0 for year <2004

The results of estimating equations 4.1 and 4.2 show that the reduction in the contribution to growth from the residual is broadly shared across countries and regions (Table 4). The post-structural-2004 change in the contribution is negative in nearly every region and for 17 out of 20 countries in the sample. It is significantly negative at the 5% or greater level of significance for 14 of the 20 countries. The negative shift in the contribution to growth is strongest and most consistent for Europe and is consistently strong for countries across all regions except Asia. A significant negative shift for the United States, the Antipodes, and the Nordic countries rules out an effect specific to the Euro area or the European Union.

The primary exception to the trend is Asia (Japan and South Korea). The more positive trend for the post-2004 Asia residual is dominated by South Korea, where strong positive health care spending growth post-2004 coincides with a rapid decline in the out-of-pocket share of

²¹ The OECD ex US residual includes relative medical price, which will also be subject to country and region-specific dynamics. Although relative medical price is fundamentally a function of input price inflation and relative growth in TFP, it can deviate from these fundamentals due to policy effects or (for market systems) factors such as industry consolidation that influence provider markups. Markets for inputs to health care respond to health system variations, but are also linked to the macroeconomy, and are likely to be regionally correlated.

health care spending, from over 50% in 1997 to 32% in 2019. This is a pronounced contrast with the OECD sample as a whole, where the out-of-pocket share is low and relatively stable, declining from 20% in 1997 to 17% in 2019. The rapid decline in the South Korean out-of-pocket share suggests underlying changes in the structure of health insurance coverage that are likely to be less than fully captured by the rough proxy of average out-of-pocket share in our model – a probable explanation for faster growth in health spending per capita for South Korea in comparison with other countries in the sample.

In sum, we see a broad reduction in the contribution from the residual to health care spending trend that is shared across 17 of the 20 countries in our sample, and across multiple regions of the world. The residual contribution exhibits a pattern of consistent fluctuations around a reduced mean contribution to growth following the structural breakpoint in 2004. These characteristics are consistent with the attribution of the structural break in the residual to a systematic change in the role of medical technology as a driver of growth. This reduced contribution could possibly include interaction effects with changes in insurance coverage that are not well captured by our out-of-pocket proxy. If the post-2004 reduction in the contribution to growth in health care spending from the residual is sustained in the future, it implies a substantially lower slope for the health share of GDP relative to historical trend – a pronounced bending of the curve.

6. CONCLUSIONS

Our results confirm the importance of income growth – and its interaction with technology – as dominant drivers of medical spending growth. Given the lag in its effects on health care spending relative to economy-wide growth, income effects explain a major part of the worldwide global slowdown in health care spending growth following the Great Recession. This element of slower growth, however, is temporary. The other underlying drivers of medical price inflation also imply that its near-zero growth rate from 2009-2019 in the US is unlikely to endure. Although the positive effect of population aging will probably endure through mid-century, the contribution to growth associated with the shared cross-country residual shows evidence of a structural break in the early 2000s that explains a substantial part of recent slower growth in the health share of GDP in both the US and elsewhere.

Rising aggregate income has enabled spending on a vast array of new drugs, procedures, and devices throughout the OECD countries. In taking an increasing bite out of national incomes, the gains in medical technology have also generated pressure to contain this spending. The average net benefits of medical innovation are likely large, but the picture for specific technologies and particular patient populations may be much less favorable and the marginal benefits may be small (Chandra and Skinner 2012). Incentives to condition the direction of research efforts with an eye towards spending implications appear to have grown with the increasing share of GDP going to health care. The consistent negative trend in the contribution of exogenous effects of technology to spending growth and its shared nature across developed economies hint at an evolution in the nature of medical innovation that places a larger emphasis on cost-reduction rather than capability-enhancing innovation.

We conclude with a cautionary note. We are well aware, as Yogi Berra said, that prediction is hard, especially about the future. Nonetheless, our results point to a durable bend in the curve of health care cost growth – assuming that medical technology persists along the dampened trajectory that has been sustained for the past fifteen years.

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Table 1: Estimated model coefficients and adjustment for income x medical price interaction

Step 1:	Estimation of Equations 2.1 and 2.2 20-country sample¹, 1970-2019				
	β_y		β'_y		$\beta'_y - \beta_y$
Estimated coefficient (standard error) ²	0.8848 (0.0351)		1.3380 (0.0081)		0.4531 (0.0361)
Step 2:	Estimation of income x relative medical price interaction effect, 14-country sample³, 1970-2019				
Estimated coefficient (standard error) ²	β_y^b	λ	$\beta_y^{b'}$	λ'	
(a) Excluding Baumol variable ⁴ (standard error) ²	0.7165 (0.0489)		1.3188 (0.0236)		
(b) Including Baumol variable (standard error) ²	0.6333 (0.0567)	0.6720 (0.0958)	1.2813 (0.0342)	0.3898 (0.1348)	
Adjustment ratio =row (b)/row (a)	0.8838		0.9716		
Step 3:	Adjustment of β_y and β'_y for income x relative medical price interaction effect + definition of estimated range for elasticities				
	Income elasticity⁵			Expenditures elasticity⁵	
Low (adjusted)	0.7821			1.2999	
High (unadjusted)	0.8848			1.3380	

¹ Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Iceland, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, US.

² White cross-section (period cluster) standard errors and covariance, adjusted for degrees of freedom

³ Australia, Austria, Belgium, Canada, Denmark, France, Germany, Japan, Netherlands, Norway, Portugal, Spain, UK, US

⁴ The Baumol variable is defined as the log of the ratio of economy-wide compensation per labor hour to GDP per labor hour.

⁵ The income elasticity is based on equation 2.1 (including two-way fixed effects by country and year); the expenditures elasticity is based on equation 2.2 (omitting period fixed effects); see text.

Table 2: Share of Growth in Real per Capita Spending on Health Consumption Expenditures Attributed to Causal Factors, 1970–2019 and 2009-2019 (percent of total)

1970 to 2019					
	United States			Simplified decomposition ²	
	Estimated range ¹		Midpoint	US	OECD exUS (midpoint of range)
(a) Income effect	36.6%	41.5%	39.0%	39.0%	52.2%
(b) Demographic change ³	8.5%	8.5%	8.5%	8.5%	12.9%
(c) Insurance coverage ⁴	6.2%	6.2%	6.2%	6.2%	2.1%
(d) Relative medical price ⁴	5.6%	10.3%	7.9%		
(e) Technology [=100-(a+b+c+d)]	43.1%	33.6%	38.3%		
(f) Income-Technology Interaction	24.3%	21.2%	22.7%	22.7%	30.4%
(g) US Technology Residual [=100-(a+b+c+d+f)]	18.8%	12.4%	15.6%		
(h) OECD exUS residual [= 100-(a+b+c+f)]				23.5%	2.4%
2009 to 2019					
	United States			Simplified decomposition ²	
	Estimated range ¹		Midpoint	US	OECD exUS (midpoint of range)
(a) Income effect	39.2%	44.3%	41.8%	41.8%	61.6%
(b) Demographic change ³	29.1%	29.1%	29.1%	29.1%	35.1%
(c) Insurance coverage	6.0%	6.0%	6.0%	6.0%	0.5%
(d) Relative medical price	-6.6%	-6.6%	-6.6%		
(e) Technology [=100-(a+b+c+d)]	32.3%	27.1%	29.7%		
(f) Income-Technology Interaction	25.9%	22.7%	24.3%	24.3%	35.9%
(g) US Technology Residual =100-(a+b+c+d+f)	6.3%	4.4%	5.4%		
(h) OECD exUS residual = 100-(a+b+c+f)				-1.2%	-33.1%

¹ Estimated range for relative medical price is based on low and high assumptions for the contribution of income and medical price for the period of imputed price inflation (1970 to 1995); see text. Estimates for 2009-2019 reflect medical price data for which no imputation is necessary and hence we show no range for relative medical price.

² The simplified decompositions do not control for relative medical price effects, which are therefore included in the OECD exUS and comparable US residuals in row (h).

³ The US and OECD exUS demographic indices have definitional differences described in the text that could account for some or all of the increased share of growth attributable to demographics in the OECD exUS sample.

⁴ Using an alternative estimate of -0.18 for the price elasticity implies a larger contribution to growth from expanding insurance coverage (11.1% versus 6.2%), and a smaller contribution from relative medical price inflation (7.2% versus 7.9%) for 1970 to 2019.

Table 3**Growth in Two Measures of Relative Medical Price Inflation, Disaggregated to Measure Contributions to Growth from Capital, Labor, Intermediate Inputs, and Medical Care TFP**

		<u>1996 to 2010</u>	<u>2010 to 2019</u>	Difference
Relative medical price (CMS)*		0.9%	-0.3%	-1.3%
Relative medical price (BLS TFP estimates)*		<u>0.9%</u>	<u>0.0%</u>	<u>-0.8%</u>
	<u>Factor shares (2010)</u>			
All inputs		<u>0.9%</u>	<u>-0.2%</u>	<u>-1.1%</u>
Capital	16.4%	0.3%	-0.1%	-0.5%
Labor	36.5%	0.2%	-0.1%	-0.3%
Intermediate inputs	47.1%	0.3%	0.0%	-0.3%
TFP		0.0%	-0.2%	-0.1%

*CMS and BLS TFP medical care price deflators are based on different methodologies. Long term growth between the two measures corresponds closely; from 1987 to 2019 the growth differential is less than 0.1 percentage point.

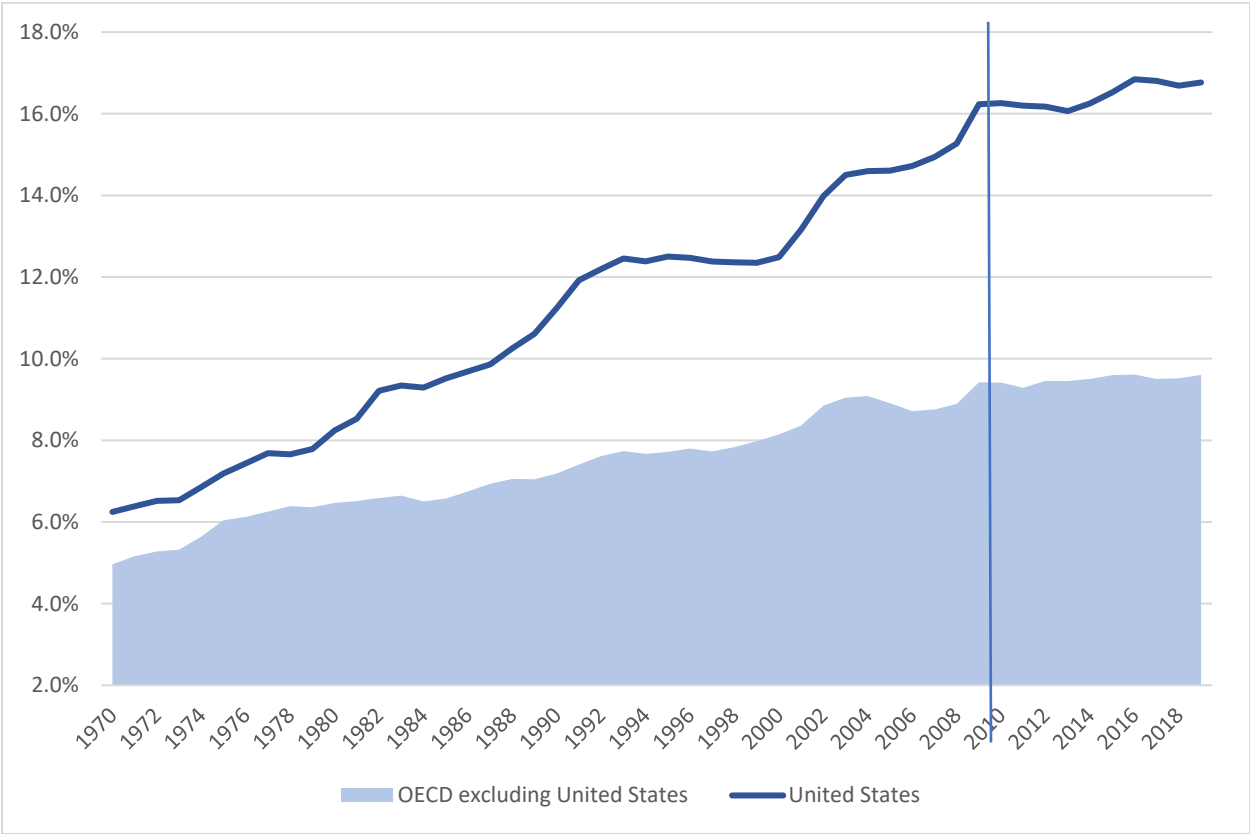
Table 4: Regional Pattern of Structural Break in Simplified OECD Residual, post-2004

	Change in contribution to spending growth from residual, post-2004	SE¹	t-statistic
OECD 20-country sample	-0.87%	0.08%	-11.15
North America	-0.47%	0.15%	-3.22
United States	-1.04%	0.18%	-5.72
Canada	0.21%	0.21%	1.00
Western Europe	-1.35%	0.11%	-11.99
Austria	-1.87%	0.17%	-11.31
Germany	-0.84%	0.26%	-3.18
Switzerland	-2.84%	0.30%	-9.45
France	-0.84%	0.24%	-3.49
Belgium	-1.30%	0.32%	-4.08
Netherlands	-0.59%	0.12%	-4.74
United Kingdom	-1.20%	0.27%	-4.38
Southern Europe	-1.63%	0.33%	-4.96
Portugal	-2.09%	0.44%	-4.74
Spain	-1.16%	0.35%	-3.32
Northern Europe	-1.15%	0.20%	-5.89
Denmark	-0.15%	0.39%	-0.38
Sweden	-1.42%	0.33%	-4.25
Finland	-0.50%	0.20%	-2.53
Norway	-0.62%	0.61%	-1.02
Iceland	-3.07%	0.49%	-6.30
Antipodes	-0.79%	0.30%	-2.67
Australia	-1.15%	0.21%	-5.37
New Zealand	-0.44%	0.58%	-0.76
Asia	1.71%	0.46%	3.75
Japan	0.85%	0.53%	1.59
South Korea	2.58%	0.62%	4.19

¹ White cross-section (period cluster) standard errors and covariance, adjusted for degrees of freedom

Shaded: countries where the post-2004 change in mean contribution to growth is negative and statistically significant at 5% level

Figure 1: Health Care Spending as a Percent of Gross Domestic Product for United States and a 19-country* OECD sample excluding the US

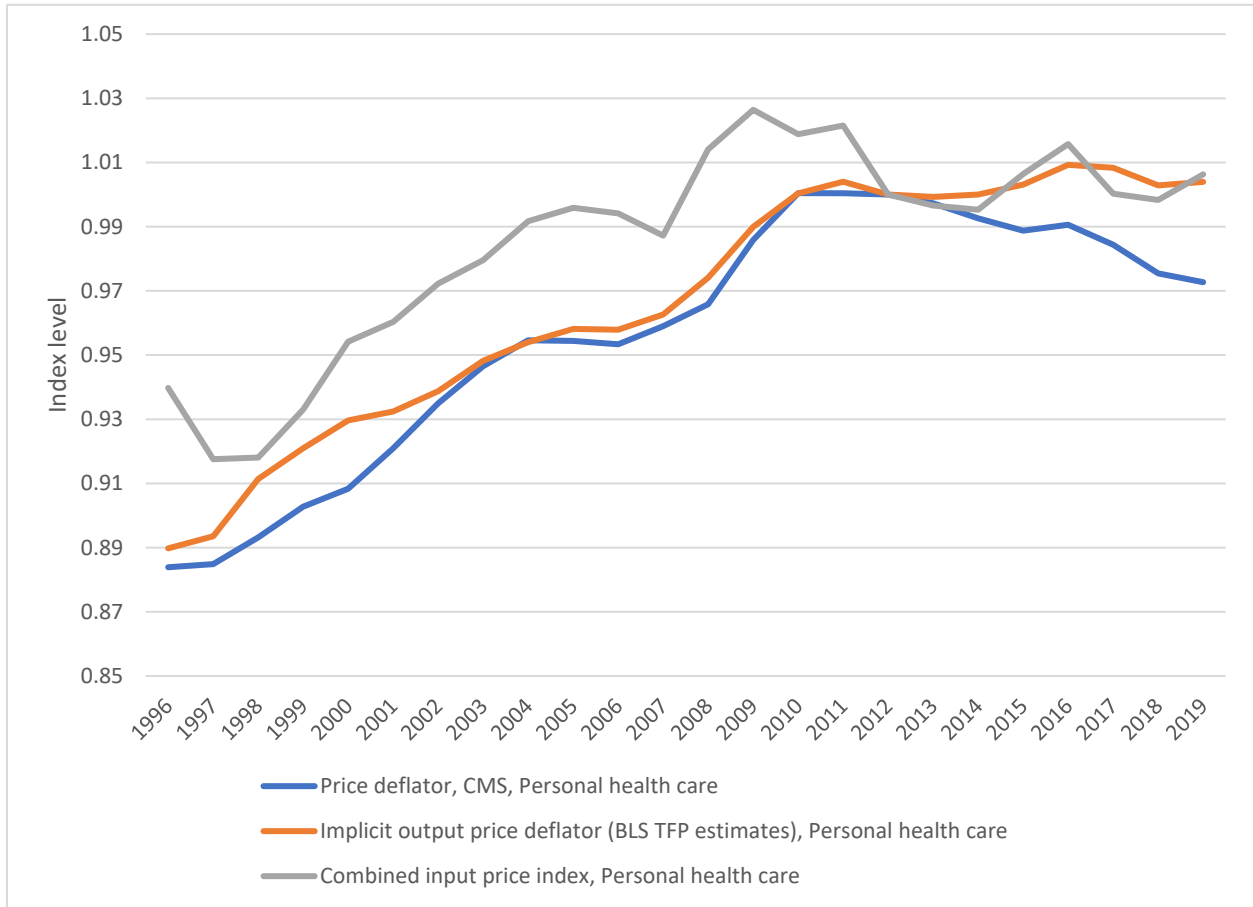


Sources: See text.

* Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Iceland, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK.²²

²² This sample of countries are those with available data from 1970 to 2019.

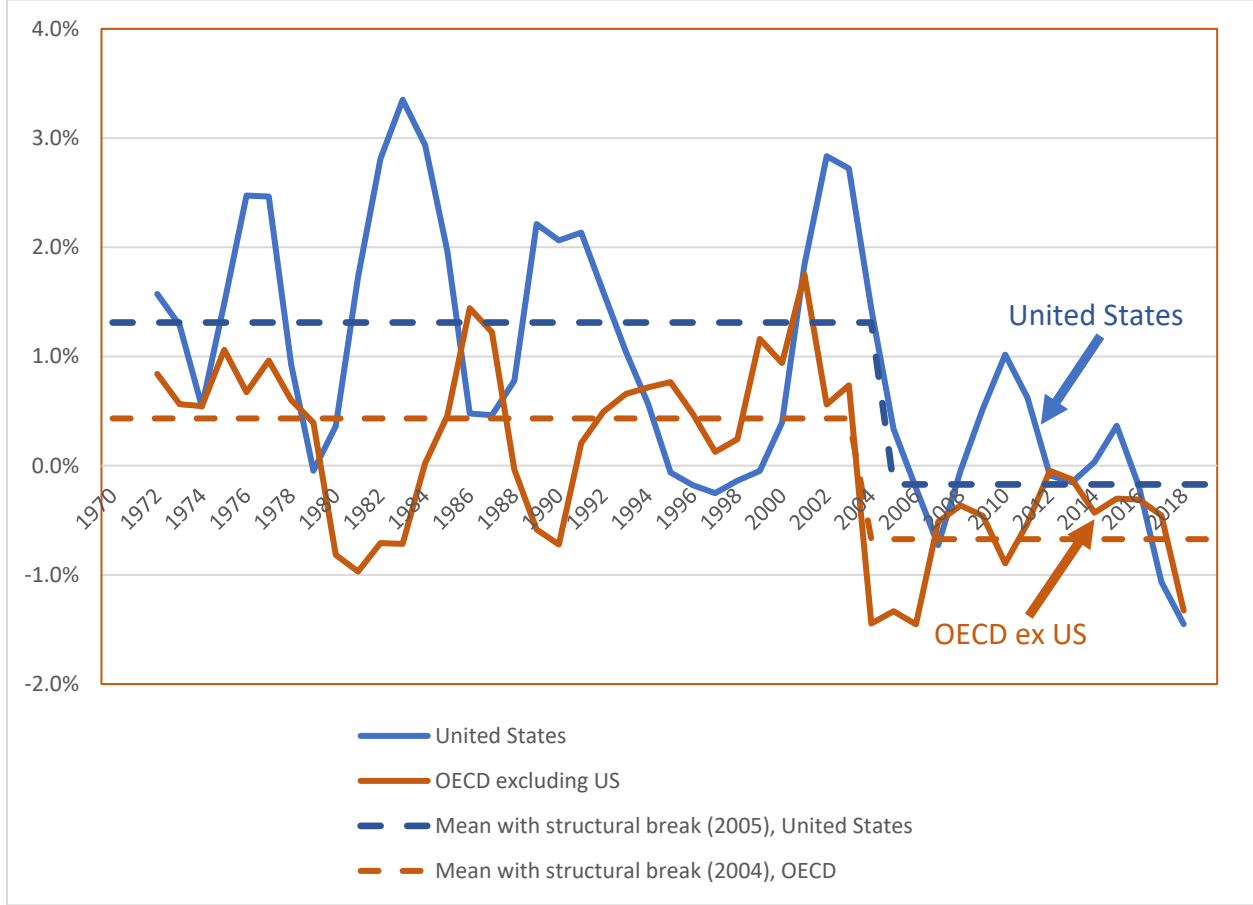
Figure 2
Relative Output Price and Relative Input Price (relative to GDP deflator), Personal Health Care
 (Index, 2012=1.0)



SOURCES:
 Centers for Medicare and Medicaid Services, Office of the Actuary, National Health Statistics Group; and Bureau of Economic Analysis and Bureau of Labor Statistics.

NOTES:
 CMS chain-weighted price deflator, personal health care
 BLS sectoral output price deflator for the calculation of sectoral measures of total factor productivity.
 Deflator for the calculation of relative output and input price inflation is the GDP deflator.

Figure 3: Contribution to Health Care Spending Growth from Residual
 (3-year centered moving average, with mean contribution before/after estimated structural break)



Source: Authors' calculations.