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Productivity Growth in the U.S. Medical Care Sector: An Analysis Using the U.S. Bureau of Economic Analysis' Health Care Expenditure Statistics by Condition

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Abstract Understanding health care productivity is critical, as the sector accounts for about 17% of U.S. GDP. However, official statistics likely understate productivity growth by failing to capture improvements in medical technology and treatment quality. The Health Care Expenditure Statistics by Condition (HCESC) developed by the U.S. Bureau of Economic Analysis address this gap by measuring spending by condition, enabling more meaningful output measurement. We present a simple framework combining the HCESC with population health data to adjust prices and output for quality improvements. Output is defined as marginal health gains rather than service counts, consistent with prior recommendations. This approach approximates more comprehensive methods while remaining tractable. Our results suggest substantial quality-adjusted productivity growth that is largely masked in official statistics, implying a downward bias of about 1.5 percentage points annually, with a range from 0 to over 5 points. Productivity gains may be larger in other high-income countries, where life expectancy has risen more and spending has grown more slowly.

Keywords Productivity, quality-adjusted prices, medical care

JEL codes E31, O47, I10

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1. Introduction

U.S. medical care spending has grown from 5% of gross domestic product (GDP) in the 1960s to 17% in 2023.[2] Because health care is such a large part of the economy, measures of health care inflation, output, and productivity can have meaningful impacts on the corresponding economy-wide measures that are used by policymakers setting budgets, businesses making investment decisions, and other users of official statistics, like those making monetary policy decisions. While U.S. government statistical agencies apply quality-adjustment methods to measure prices and output in other high tech sectors of the economy, such as computers and smartphones, there is no quality adjustment for the health sector. However, life expectancy has grown by nine years over this period, and it is thought that much of the gain in life expectancy is driven by spending on new innovations that improve health outcomes.[3] For example, more effective treatments for cardiovascular conditions, cancers, hepatitis C, HIV, and rheumatoid arthritis have extended life expectancy and improved quality of life around the world. If medical care is driving these changes in life expectancy, then many prominent papers argue that this spending is "worth it" and productivity is increasing rapidly, at least in some circumstances (Cutler and McClellan, 2001; Cutler et al., 1998; Hall and Jones, 2007; Murphy and Topel, 2006). However, the unadjusted measures for health care imply weak or negative productivity growth for the past several decades. According to the U.S. Bureau of Labor Statistics (BLS), annual total factor productivity growth from 1990 to 2019 for health care and social assistance (NAICS 62) has fallen by 0.6% per year.[4]

Currently, official statistics on health care track spending across broad service categories like hospitals, physicians, or prescription drugs, which provide limited insights into many key developments in the health sector. Namely, these aggregate figures obscure wide variation in treatments as individual diseases are associated with distinct treatment technologies. For instance, while treatments for the common cold have changed little over the past century, therapies for other conditions, such as cancers, cystic fibrosis, and multiple sclerosis, would not be recognizable from three decades ago. Grouping such diverse conditions and treatments into the same category is akin to combining the agricultural and high-tech sectors of the economy — it conceals fundamental shifts and innovations. This service-based framework has two main shortcomings. First, it fails to capture substitution patterns across medical industries in the treatment of particular conditions. For instance, shifting from costly inpatient hospital care to outpatient visits can substantially reduce treatment costs, yet such changes are not reflected in official statistics (Aizcorbe and Nestoriak, 2011). Second, it ignores the unique technologies associated with each condition, limiting the potential to make meaningful quality adjustments.

This limitation of official statistics led to the development of the Health Care Economic Statistics by Condition (HCESC, formerly known as the Health Care Satellite Account) at the U.S. Bureau of Economic Analysis (BEA). Unlike traditional statistics that primarily track health care inputs (e.g., hospitals, offices and prescription drugs), the HCESC redefines output to be the treatment of a condition, essentially treating each condition as its own industry (National Research Council (2011) and Cutler et al. (2022)). Under

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[2] The growth in the share of spending by the health care sector is from BEA (growth in the share of spending).

[3] See the National Center for Health Statistics (https://www.cdc.gov/nchs/data/hus/2020-2021/LExpMort.pdf).

[4] In more recent years, total factor productivity growth has been flat for NAICS 62, with an annual growth of 0.16% over the 2000-2019 period, but hospital and nursing care productivity (NAICS 622-623) has continued to fall. See Tables from the U.S. Bureau of Labor Statistics.

traditional accounts, output rises with service volume; but under the HCESC, output rises with number of patients treated. The statistics track spending, the price of treatment, and output for about 260 medical conditions (Dunn et al. (2015)). This framework appropriately treats hospitals, physicians, and prescription drugs as inputs into the treatment of a disease, rather than outputs, and allows for detailed insights into the diverse patterns of health care spending across different conditions. Indeed, health economists and measurement experts have long advocated for measuring the health sector output by the treatment of a condition for these reasons (Berndt et al. (2000) and National Research Council (2011)). However, a current limitation of the HCESC is that it does not account for quality changes brought about by improved technology.

In this paper, we first derive key measurement concepts, such as quality-adjusted prices, output, and productivity. We define nominal output as expenditures on medical treatments, and apply a price index derived by Cutler et al. (1998) and Fisher and Shell (1972) to measure real output. This utility-based price index captures the compensating variation necessary for patients to maintain the same level of utility across periods. Consistent with Cutler et al. (1998) and Cutler et al. (2022) the utility derived from medical care includes benefits (e.g., improved health due to treatment) and costs of treatment. While the HCESC is consistent with United Nations System of National Accounts (SNA) 2025 goal of creating extended accounts that offer more detailed insights into the health care sector, the approach we take in this paper deviates from the standard SNA methodology and is closer in spirit to the GDP-B framework outlined in Brynjolfsson et al. (2019), which aims to better capture the full benefits of economic production. More specifically, the work more closely follows the recommendations of National Research Council (2011) and Sheiner and Cutler (2024) that outline methodologies for improving measurement in the health care sector.

We then demonstrate how to construct approximate quality-adjusted estimates of prices, output, and productivity using publicly available data. Our quality-adjusted price index is constructed using estimates of the price of treatment from the HCESC, per capita health expenditures from the National Health Expenditure Accounts (NHEA), and life expectancy estimates from the National Center for Health Statistics (NCHS). In our analyses, we use aggregate (i.e., across all conditions) life expectancy improvements to quality adjust our aggregate price and output measures. The life-expectancy measure may reflect changes in population health due to nonmedical factors.[5] To account for nonmedical determinants of life expectancy, we incorporate information from Cutler et al. (2022), which develops a methodology for disentangling changes in health due to medical care from other factors.

This paper builds off of a much broader agenda to improve the measurement of health and health care (National Research Council (2011) and Sheiner and Cutler (2024)), which includes numerous contributions in health-related literatures.[6] More specifically, this paper builds on work by Cutler et al. (2022) and

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[5] It is important to recognize that health outcomes are determined by numerous factors (including but not limited to behavior and genetics), and that research suggests that medical care accounts for a fraction of the variation in health outcomes. For example, health care (or lack thereof) explains something like 10% of premature mortality in the U.S.; see, among others, Schroeder (2007), Nolte and McKee (2011) and Kaplan and Milstein (2019). The social determinants of health (e.g., housing stability) are an important driver of outcomes, and have received considerable scholarly attention (Marmot and Wilkinson (2006); Sheiham (2009); Braveman et al. (2011); Bhat et al. (2023))

[6] This includes literatures in cost effectiveness, health services, health policy and health economics. For example, the seminal Dartmouth Atlas of Health Care has documented and investigated widespread variation in how health care is delivered across the United States, in turn motivating a wide range of studies in allied health fields(Wennberg et al., 1996; Fisher et al., 2003a,b). This geographic variation has raised critical questions about why certain areas perform differently than others, leading scholars to assess, among other things, the role of low-value care (see, e.g., (Chant et al., 2023)).

Weaver et al. (2022) who have developed in-depth methodologies which capture disease-specific changes in quality. However, these studies require complex methodologies and very detailed data. Our contribution is to demonstrate an approximation to these studies with readily available data sources to provide top-line analysis. In theory, this provides a starting point for more timely and transparent estimates, which is an important goal of statistical agencies. Furthermore, we extend Cutler et al. (2022), which focuses on the aged 65+ population (due to data availability), to the entire population. We find that measuring the entire age distribution makes a large difference in our productivity estimates. Much of the medical care we consume at earlier ages extends or improves life beyond the age of 65. In productivity terms, many of the health production function inputs occur before 65, while many of the outputs (health improvements) accrue to those older than 65. Hence, our results suggest that a productivity measure should capture inputs made throughout the life cycle.

Our central estimates show quality-adjusted prices fall by about 1.3 percentage points per year relative to economy-wide inflation over the period from 2000 to 2019. This is about 1.7 percentage point below the official index for the sector (the personal consumption expenditure (PCE) health price index), indicating output and productivity are understated by a similar amount.[7] Adjusting the baseline estimate of productivity from BLS to account for the improvement in quality, we estimate productivity growth of about 1.7% per year, which is much higher than the official estimate of 0.16% per year for the health care and social assistance sector.[8] The estimate is sensitive to the value placed on a healthy year of life, as well as assumptions about how much of the change in health is due to medical care versus other factors. Over a wide range of assumptions, our estimates of the quality-adjusted price index ranges from 0.2% to -7.6% per year, relative to economy-wide inflation. However, the range of spending per healthy life year saved is between $70k and $115k, suggesting sizable financial cost for improved health, which should be of key interest to policymakers that must consider both limited budgets and the opportunity cost of these expenditures. Although it is important to note that the higher cost is arguably "worth it" as these amounts are substantially below the typical value placed on a healthy life year, which is usually over $150k (Kearsley (2024)).

The approximation presented here provides a top-line estimate which relies on more aggregate assumptions, providing an independent range of estimates to better understand the productivity of the sector. If we apply our estimates to the over-65 population, we find productivity growth estimates that are much larger than our baseline findings. The likely reason is that the share of health spending for those under 65 is relatively large compared to the improvement in health outcomes they experience. Those under 65 account for 53% of the lifetime health care spending. Meanwhile, most of the health gains in life expectancy go to those 65 and over. Over the period we study, life expectancy increased 1.7 years for the 65 and over population, and 2.0 years for the full population, only an additional 0.3 years. One interpretation is that medical care spending under 65 is less productive. However, medical care spending under 65 is often an investment to lengthen one's life or improve life after 65, as in the seminal paper by Grossman (1972). For this reason, one would want to measure health care spending across the entire age distribution to measure productivity. While this is a small extension, it makes a meaningful impact in our price index and productivity estimates:

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[7] BEA's PCE health price index tracks prices for health care goods and services consumed by households and reflects payments by consumers, insurers, and government programs, and is used to measure inflation in the health sector within the national accounts.

[8] This productivity figure is for the period 2000 to 2019, while the negative productivity growth mentioned in the first paragraph is from 1990 to 2019. More generally, the productivity for the sector is typically flat or declining slightly.

our price index estimate grows -2.1% per year when using only the 65 and over population versus -0.7% annually when measuring the entire age distribution.[9]

As an alternative to using population health outcomes, Eggleston et al. (2020); Dunn et al. (2022); Cutler et al. (2022); Dunn et al. (2024) use measures of clinical effectiveness of technologies from the medical literature to measure quality changes. Additional evidence based on acute health conditions, where the role of medical technology is more clear, also provides additional supporting evidence of the productivity change (see Cutler et al. (1998), Romley et al. (2020) and Dauda et al. (2022)). We find that these alternative approaches are generally consistent with the approximation presented in this paper.

The estimates presented in this paper are useful to better gauge the potential bounds of mismeasurement in aggregate statistics, as well as understanding the costs of health improvement in the aggregate. However, these aggregate estimates do not reveal heterogeneous productivity differences in health care spending across populations or conditions, limiting its usefulness for health care management decisions.

While significant progress has been made in this literature, there are several important caveats. The first is that the measure of productivity presented here is based on utility theory and consumer welfare, and is distinct from methods applied elsewhere in the accounts (see Dynan and Sheiner (2018)). The focus on welfare measurement more closely aligns with the GDP-B approach of Brynjolfsson et al. (2019). This approach departs somewhat from the SNA 2025, which focuses on the measurement of outputs from economic activity rather than outcomes. However, the distinction between output and outcomes blurs in the health sector as the quality-adjusted price and output depend on the expected outcome of treatments, although not (as a conceptual matter) outcomes due to nonmedical factors. This distinction is important as policy implications for changes in outcome due to medical care are different for changes in outcomes due to changes in population health. A second caveat is related to the interpretation of the estimates. Evidence that productivity is improving does not necessarily imply that health spending is optimal from a welfare, budgetary, or incentive standpoint. Although the benefits appear to exceed the cost in our baseline estimates, this does not preclude the existence of alternative scenarios — such as lower spending or better health outcomes — that might generate even greater productivity gains. Additionally, policymakers may interpret these estimates differently based on their policy objectives. Some may focus primarily on short-term consumer welfare, while others might prioritize ensuring adequate incentives for firms to invest and innovate that could potentially lead to larger long run welfare gains. Despite potentially different interpretations, providing such statistics equips policymakers with crucial information to make more informed decisions.

2. Health Care Economic Statistics by Condition

Each medical condition warrants distinct treatments, underscoring the value of the condition-specific data in the HCESC. The HCESC estimates start with nationally representative survey data from the Medical Expenditure Panel Survey (MEPS), which collects detailed information on about 30,000 individuals per year,

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[9] This number differs from the -1.3% number in the previous paragraph because it assumes a value of a statistical life year (VSLY) of $100k to match Cutler et al. (2022).

their treatment expenditures, medical conditions, and associated expenditures across all service types. While the sample size may seem large, it is actually relatively small when analyzing trends for specific conditions (see Dunn et al. (2015)). For this reason, the HCESC combines MEPS with large claims databases. For the privately insured population, BEA uses the Merative™ MarketScan® Research Databases claims, which is a convenience sample of the privately insured population. For Medicare beneficiaries, the HCESC uses claims data from the Center for Medicare Medicaid Services (CMS). For the remaining population, including Medicaid enrollees and the uninsured, the HCESC uses MEPS data. Each claims data source adds millions of enrollees and billions of claims to the estimates, and population weights are applied to maintain the representativeness of the estimates. The large sample size is necessary for capturing patterns for conditions that are costly but relatively rare in the population, such as cystic fibrosis.

In addition to tracking nominal spending by condition, the HCESC includes a price index that measures the price of treating a condition. It is measured as the total expenditures to treat a patient for a year. For example, for heart disease the treatment price for a patient would include all care in a year, such as doctor visits, labs, scans, hospital visits and prescription drugs. Figure 1 shows the trend in the price of treatment for select conditions, deflated by the aggregate PCE deflator. The figure shows that the price of treating medical conditions can vary substantially over time. For example, treatment costs for rheumatoid arthritis, hepatitis, and cystic fibrosis surged as new, higher-quality drugs entered the market, followed by a sharp decline in hepatitis spending around 2015 due to increased competition among innovative drugs. In contrast, spending patterns for diabetes and heart disease were relatively flat and actually declined relative to economy-wide inflation.[10]

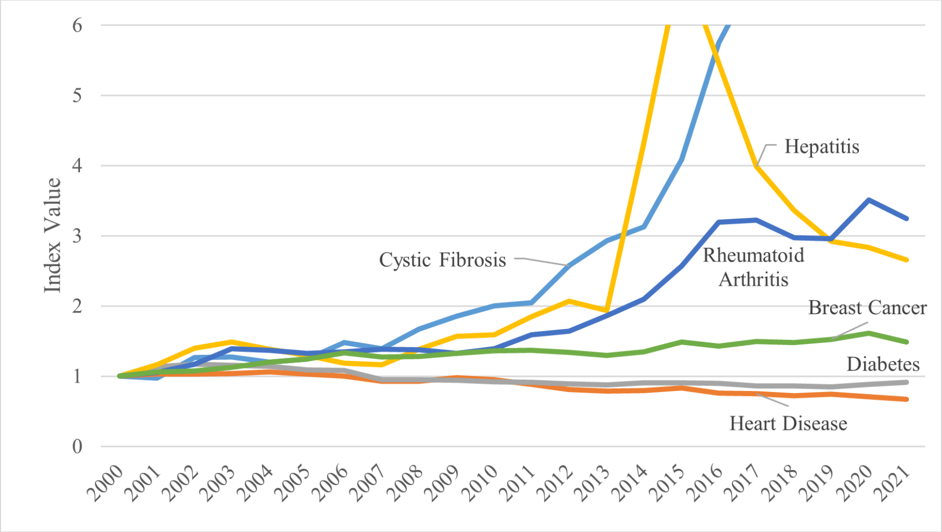

Figure 1. HCESC-based Price Index for Select Conditions

Notes: This figure shows trends for disease-specific price indexes from the BEA HCESC.

Understanding spending patterns by condition can be useful for many questions that have important policy implications. What conditions account for the greatest share of spending? What conditions are driving expenditure growth? Or slowing it down? How do these changes relate to regulations, innovations, pop-

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[10] This decline for heart disease coincides with a period over which many drugs to treat heart disease lost patent protection. This pattern is also consistent with Lichtenberg (2024), which finds that in the long run, pharmaceutical innovations can lead to lower costs of treatment.

ulation health, or other trends in the market? Another important use of this information is to improve measures of output and productivity to better understand the value of medical care spending. Condition-specific data make it easier to improve measures of output and productivity, as treatment technologies — and their associated costs and quality improvement — are often unique to each condition. This, in turn, allows for a more accurate assessment of the value of medical care spending. In addition, the HCESC more appropriately handles inefficient spending, relative to traditional methods. The traditional methods count output as growing as more services are provided, so inefficient spending leads to higher output. The HCESC output grows only with the number of patients, so an increase in inefficient spending per patient leads to a higher price of treatment and does not increase output.

One advantage of the condition-based price measure over traditional service-based price index measures is that it redefines the output to be the treatment of a condition, which better handles substitution patterns across different types of inputs, as highlighted by Aizcorbe and Nestoriak (2012).[11] Aizcorbe and Nestoriak (2012) demonstrate that shifts could lead to cost savings, leading condition-based price indexes to grow more slowly than traditional indexes (e.g., shift from expensive inpatient services to outpatient services).[12]

Alternatively, if more expensive new technologies are used in treatment, this could lead the condition-based index to rise more quickly than the traditional PCE health price measure. Specifically, if an expensive new treatment enters the market in year 2, it will not be added to the PCE index in tracking price changes from year 1 to year 2, as it tracks a fixed basket of goods and services and excludes the new treatment. In contrast, the HCESC will increase in year 2 when the new treatment replaces older, cheaper treatments. If the new and higher price technology is also of higher quality, both indexes will be biased, but the HCESC may appear to have a larger bias, as the new technology leads to a bigger increase in the index, relative to the PCE health measure.

Theoretically, either effect (e.g., shifting services to cheaper settings, or new innovative treatments raising costs) could dominate, but as shown in Figure 2, the condition-based price index tends to grow faster than the traditional PCE health price index, highlighting the role of technology likely driving up the cost of treatment. In fact, the condition-based price index grows faster in many cases because of the adoption of newer and costlier technologies, such as for the treatment of several of the conditions shown in Figure 1. At the same time, micro evidence shows shifts toward higher quality treatments. Dunn et al. (2024) examine innovations for 13 health conditions and show that there is a tendency for consumers to gravitate toward higher quality new treatments, even if those treatments are substantially more expensive. Chandra et al. (2016) show that patients gravitate to higher quality hospitals over time, even for acute health conditions. This fact highlights the need to properly quality adjust condition-based price indexes.

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[11] Aizcorbe and Nestoriak (2012) is the first paper to construct condition-based estimates using claims data providing an important foundation for the development of the HCESC.

[12] In this case, if there is no quality change, then the condition-based index would more accurately capture inflation, relative to the official PCE health price index, which measures the cost of a basket of specific goods and services year over year.

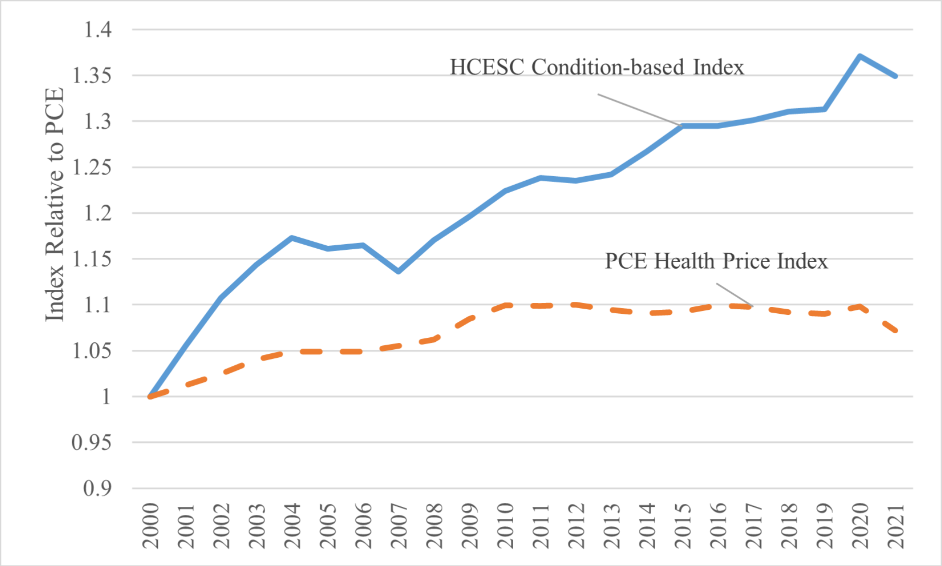

Figure 2. Condition-based Aggregate Price Index (HCESC Blended Account) and Personal Consumption Expenditure for Health Price Index (in 2021 $s)

Notes: This figure shows trends for the aggregate price index from the BEA HCESC and trends in price growth from the official PCE Health by function index from the BEA. The PCE data is based on NIPA published estimates June 27, 2025. The HCESC estimate is based on estimates published in December 2-23.

3. Cross-Country Differences

This paper is focused on the U.S. experience, but there is broad international interest in this topic due to both the importance of health and the growing budget share across economies. Cross-country comparisons further highlight the link between economic measures and health outcomes. Deaton and Schreyer (2022) show a strong positive correlation between national accounts aggregates — particularly actual individual consumption — and life expectancy. While this relationship is evident, what remains largely unmeasured is how such health outcomes connect to the output and productivity of the health care sector, despite their clear significance for both economic performance and overall well-being. The challenge lies in isolating the contribution of medical care from broader nonmedical determinants of health (Sharpe et al. (2007), Schreyer (2012), National Research Council (2011), and Sheiner and Cutler (2024)).

One fact that stands out from these comparisons is that the U.S. spends substantially more on health care than most other economies, but health outcomes measured by life expectancy and some other metrics are substantially worse (Foundation (2020)). There are a variety of theories regarding what drives these differences, including administrative costs, pricing, adoption of high-cost technologies, heterogeneity in treatment across the population, and differences in underlying population health (Garber and Skinner (2008), Cutler and Ly (2011), Chandra and Skinner (2012), and Einav and Finkelstein (2023)). While aggregate statistics suggest that the health sector in the U.S. is less efficient, several studies suggest that obesity in the U.S. may contribute substantially to its measured lower life expectancy, complicating these comparisons (Preston and Stokes (2011) and Mokdad et al. (2024)). In order to conduct comparisons in the productivity of health systems over time or across countries, it is necessary to account for the differences in population health affecting both outcomes and spending to better isolate the effects of the health care sector on health outcomes and spending. In this paper, we focus on the productivity in the U.S. over time.

4. Literature

This section highlights some key insights relevant to measuring productivity in the health sector. For a more comprehensive review of the literature, see Hall (2017), Sheiner and Malinovskaya (2016), and Sheiner and Cutler (2024).

This paper focuses on a utility-based measure of productivity, where we show the change in output per treatment depends on improved health. Alternative methods tend to greatly understate the value of health improvements, as highlighted in several recent papers (Sheiner and Malinovskaya (2016), Dauda et al. (2022), and Dunn et al. (2022)). Additionally, hedonics used in other industries, like computers or smartphones, are poorly suited to the health care sector, where there are numerous market distortions and consumers rarely face the marginal cost of treatment (Berndt et al., 2000).

There is broad evidence that quality of treatments is improving over time, leading to improved health outcomes. The evidence is supported by studies using population health to measure quality, those using evidence from the clinical literature, and studies examining acute health conditions (see Sheiner and Cutler (2024) for a recent overview). Outside of the U.S., recent evidence from Park et al. (2025) shows large quality improvements in South Korea, likely attributable to improvements in the health sector. Eggleston et al. (2019) shows quality-adjusted prices falling for diabetes care across several countries. While many papers in this literature focused on specific health conditions, the goal of our paper is to obtain an estimate of an aggregate quality-adjusted price index for the U.S.

The methodology to derive a quality-adjusted price and productivity relies on the dollar value placed on improved health (see Viscusi (2020) for a review). Recent estimates of a value of a life in the U.S. range from $6 million to $20 million (Kearsley, 2024), but the exact magnitude is important for assessing the productivity gains in the sector. Using the dollar value of health from Kearsley (2024), the value for a year of health is $150k or more.[13] For our analysis below, we follow Cutler et al. (2022) and use a value of $100k for comparability. However, given the uncertainty and higher range implied by the literature, we also provide estimates using $150k and $250k per value of a statistical life year (VSLY).

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[13] Recent estimates in the literature, such as Cutler et al. (2022), do not apply discounting to spending or health improvements, which would lead to a statistical life year of $150k for a low end estimate based on figures from Kearsley (2024).

5. Measuring Output and Productivity in the Health Care Sector

Understanding the benefits alongside the costs of treatment is fundamental for measuring the productivity of the health sector, but numerous distortions in health care markets complicate standard approaches for measuring quality change. The seminal research by Cutler et al. (1998) addresses this issue by developing a framework built on utility theory that is robust to market distortions in the health care sector. We will present basic formulas for price, output, and productivity derived from this utility-based framework in this section.

5.1. Quality-Adjusted Price Index

Following Cutler et al. (1998), Sheiner and Malinovskaya (2016) and Dauda et al. (2022), let $P^j_{0,t}$ be the quality-adjusted price index for a condition j from time period 0 to t. We apply a Laspeyres-type price index that uses a compensating variation welfare formula to adjust for quality.[14] The quality-adjusted price index measures the growth in treatment expenditure from period 0 that would be necessary to maintain the same level of utility in period t, holding technology constant. Let S^j_t be the lifetime expenditure for treatment of condition j at time t.[15] Let H^j_t be the incremental amount of health produced from treatment at time t for disease j. H^j_t is often measured in terms of quality-adjusted life years (QALYs) that account for both the number of years alive and the quality of those years, where one QALY is one year of life in perfect health.[16] Importantly, H^j_t is not the actual health outcome, but the amount of health due to treatment and not other factors (e.g., diet or exercise). Both S^j_t and H^j_t are typically risk-adjusted to account for the age and health conditions of the patient, so that changes in expenditures and health outcomes are the changes from medical care, and not changes from other factors. In order to quality adjust the price of treatment, a value is needed to convert units of health into dollars. Typically, researchers apply measures from external studies that derive estimates of the value of a statistical life year, as discussed previously. Here we let the dollar value of a statistical life year be represented as $\$VQALY$ (value of a quality-adjusted life year) and, as mentioned previously, we consider the range from \$100k to \$250k. The change in quality of treatment is then, $\Delta H^j_t = H^j_t - H^j_0$, so the dollar value of the change is then: $\$VQALY \cdot \Delta H^j_t$

We follow Dauda et al. (2022) and Sheiner and Malinovskaya (2016) to compute a quality-adjusted price $P^j_{0,t}$ for condition j at time t. The price index is an index of the growth in price from the base period 0, to the end of our sample t. Intuitively, the quality-adjusted price asks how much spending in period 0 would be needed to deliver the same utility as treatment in period t. In order to hold technology constant, the

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[14] A similar Paasche-type price index could also be applied, as shown in Dauda et al. (2022).

[15] Spending needs to be measured in expected lifetime units to match the QALY measurement, which is in terms of the gain in health over a lifetime.

[16] For instance, a health condition that leads to a disability will reduce the QALY of a patient, even if the life expectancy does not change.

quality improvements must be subtracted from the unadjusted treatment price, S_t^j, in period t.

$$P_{0,t}^j = \frac{S_t^j - \$VQALY\Delta H_t^j}{S_0^j} \tag{1}$$

$$= \frac{S_t^j}{S_0^j} - \frac{\$VQALY\Delta H_t^j}{S_0^j} \tag{2}$$

The second row of the index shows that without any change in the quality of treatment, the price index measure would be a measure of the unadjusted price of treatment, $\frac{S_t^j}{S_0^j}$, which is the price index in the HCESC. Quality improvements lead to reductions in the quality-adjusted price of treatment through the adjustment term in the numerator, $\$VQALY\Delta H_t^j$. The derivation is in the appendix, but this formulation is intuitive. Consider the example of the price change from the introduction of the drug Sovaldi in 2014 used to treat Hepatitis C discussed in Dunn et al. (2022). They consider the price change compared to the prior drug interferon. Based on cost-effectiveness studies, the price of Sovaldi was $105,488, while the price of interferon was $81,211. The Quality-Adjusted-Life-Years (QALYs) from treatment is 9.4 for Sovaldi and 8.28 for interferon. As an extreme example, they place a relatively low value on the QALY of just $50,000. Based on these estimates and the utility-based price index formula, the price index falls by 39%.[17] Intuitively, the average person is receiving $56k=$50k*(9.4-8.28) of value for the health they are purchasing, at an incremental cost of $24k=$105k -$81k, hence quality adjusted prices are falling.[18]

One seemingly intuitive alternative price adjustment is to scale the price by the quality change, for example, $P_t = \frac{S_t}{S_0}\frac{H_0}{H_t}$. Intuitively, one can view this as the change in the price of a QALY. However, as pointed out in a number of recent papers (Sheiner and Malinovskaya (2016), Dunn et al. (2022), and Dauda et al. (2022)), scaling price changes by the growth in quality of treatment does not account for the value of a QALY. Here is a stylized example to highlight this. Suppose an individual with high cholesterol in 1980 has a baseline life expectancy of 10 years and their cholesterol medication cost $1,000. By 2015, statins have entered the market and gone off patent. Suppose that the same individual would now have 15 years of life expectancy, and their statins cost $2,000. This index suggests that quality adjusted prices have risen by 33 percent ($\frac{\$2000}{\$1000} \times \frac{10}{15}$), placing an implicit value of the health gain of around $670.[19] However, most economists would argue that a 5-year increase in life expectancy is worth more than several hundred dollars. Our measure differs because it places an explicit value on a year of life, while the price-per-QALY approach is orthogonal to changes in the value of a life year, as that term cancels out of the ratio H_0/H_1.

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[17] The value is derived as: 0.61=($105k - $50k*(9.4-8.28))/$81k.

[18] Note that sufficiently large quality improvements can potentially yield a negative price index. There are three primary ways to address this issue. First, Dauda et al. (2022) apply chaining, which effectively scales down incremental quality gains at each step relative to costs. A second approach is to expand on the conditions over which quality adjustments are applied. By increasing total treatment expenditures, this helps ensure that the resulting price index remains positive. If chaining is not feasible and the application requires condition-specific price indexes then a common solution is to use a reservation price index. Dunn et al. (2022) and Ackley et al. (2026), building on Trajtenberg (1990), use a reservation price index of the form: $P_{0,t}^j = \frac{S_t^j}{S_0^j + \frac{\$VQALY\Delta H_t^j}{S_0^j}}$, where the quality adjustment enters the denominator. This index ensures that improvements in technology do not generate negative prices because the denominator represents the reservation price that leaves individuals in the base period indifferent between the new and prior technologies. While all three approaches are theoretically valid, they differ in the underlying baseline utility and technology being held fixed. The approximation used in this paper follows the third approach.

[19] The unadjusted price index is 2 (i.e., $\$2000/\$1000$), while the adjusted price index that scales the price by the quality change is 1.33 (i.e., $\$2000/\$1000 \cdot 10/15 = 1.333$. If this adjustment is capturing the correct reservation price, then the expenditures necessary to make an individual indifferent to the new technology is just $1,333 dollars, so the dollar adjustment is $670 for five additional years of life.

Others in the literature have pointed out the differences between these two intuitive ways of quality adjusting health spending (Sheiner and Malinovskaya (2016), Dunn et al. (2022), and Dauda et al. (2022)). Specifically, Sheiner and Malinovskaya (2016) points out that if one assumes that the price-per-QALY is roughly the VSLY, then our indexes are the same.[20] While this type of assumption is valid in many contexts, it is often violated in health care markets. Some very cheap technologies, like generic drugs, can provide a lot of health benefits at very low costs. But, in many cases, it is not possible to buy more health, even with very high levels of expenditure due to technological constraints.

5.2. Growth in Real Output

We derive real output per case (i.e., per patient), Y_t^j, by dividing spending per case by the quality-adjusted price index.[21] Using equation 1, we have $Y_t^j = \frac{S_t^j}{P_{0,t}^j} = \frac{S_t^j \cdot S_0^j}{S_t^j - \$VQALY\Delta H_t^j}$. Let the number of cases be N_t^j in period t and the number of cases be N_0^j in period 0. Total real output in period t is $N_t^j \cdot Y_t^j$ and the real output in the base period is $N_0^j \cdot Y_0^j = N_0^j \cdot S_0^j$. Therefore, the index of quality-adjusted total real output growth, reflecting real personal health care consumption, is:

$$\frac{N_t^j \cdot Y_t^j}{N_0^j \cdot Y_0^j} = \frac{N_t^j \cdot S_t^j}{N_0^j \cdot S_0^j \cdot P_{0,t}^j} = \frac{N_t^j \cdot S_t^j}{N_0^j \cdot (S_t^j - \$VQALY\Delta H_t^j)}. \tag{3}$$

The index measure of real output growth is an increasing function of the health gained from the treatment: ΔH_t^j that is scaled to a dollar value, times the growth in the number of cases. If the quality does not change, then the output growth does not depend on the amount spent on treatment, but only the number of treatments. If quality does change, then an adjustment is needed to convert output per case in the base period to the output per case in period t. It is worth emphasizing that this is a stark difference from more traditional output measures. Holding the number of cases $N_t = N_0$ constant, then the quality-adjusted output measure only increases when health from treatment improves, while traditional measures increase as more goods and services are provided (e.g., doctors visits or prescription drugs).

The growth in output is *not* proportional to the growth in health. It depends on the increase in health relative to the amount spent on the treatment.[22] For countries that do not measure output growth by deflating expenditures, the adjustment could by applied directly to an output per case growth measure in equation 3.[23]

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[20] The price per QALY formula is:

$$P_t = \frac{S_t}{S_0}\frac{H_0}{H_t} = \frac{S_t}{S_0}\frac{H_0}{H_0\left(1+\frac{\Delta H}{H_0}\right)} \cong \frac{S_t}{S_0}\left(1-\frac{\Delta H}{H_0}\right) = \frac{S_t}{S_0} - \frac{\Delta H}{S_0}\frac{S_t}{H_0}$$

If $\$VSLY = \frac{S_t}{H_0}$, then this formula matches equation 1.

[21] As applied in the U.S. National Economic Accounts, deflators are applied to obtain real output.

[22] For example, suppose a treatment cost \$20,000 in period t, but the health produced from a treatment changed from 0.5 QALY to 0.6 QALY and \$VQALY=\$100k, then based on the formula the output doubles, even though QALY increased by 20%. The intuition is straightforward, as relative to the \$20,000 in output received in period t (the numerator), the output is the base period is \$10,000 in value after accounting for the lower quality of treatment received in the base period. Patients are getting twice the output per dollar spent.

[23] Note that volume measures applied internationally are often counts for particular places of service (e.g., hospital volume or physician visit volume), whereas the volume measure here is the number of patients treated for the condition, across all

5.3. Productivity

The productivity change is determined by the growth in real output relative to the growth in inputs. Let $C_t^{N,j}$ be the nominal (input) cost per case, then to obtain the real cost per case, $C_t^{R,j}$, we divide by an input price index. The cost includes the associated cost of inputs (e.g., capital, labor and materials), and may differ from S_t^j if more output can be produced with the same level of costs. The index of real input growth is then $\frac{C_t^{R,j}}{C_0^{R,j}}$. Productivity growth is the growth in real output divided by the growth in real input:

$$ProductivityIndex_{0,t}^j = \frac{N_t Y_t^j}{N_0 Y_0^j} / \frac{N_t C_t^{R,j}}{N_0 C_0^{R,j}} = \frac{Y_t^j}{Y_0^j} / \frac{C_t^{R,j}}{C_0^{R,j}}$$

Inserting the formula for growth in real output and growth in costs we have:

$$ProductivityIndex_{0,t}^j = \frac{\frac{S_t^j}{S_t^j - \$VQALY \Delta H_t^j}}{\frac{C_t^{R,j}}{C_0^{R,j}}} \tag{4}$$

Equation 4 shows that the quality adjustment enters through the output price index, so one way to adjust the official measure of productivity is to apply an adjustment to the output price index (see Dunn et al. (2022)), which is the approach we take in the empirical section below. More precisely, we are essentially changing the deflator applied to output by multiplying the official growth in real output by the ratio of the corresponding official deflator, divided by the quality-adjusted price index.

6. Empirical Evidence

6.1. Estimates Based on the Health Care Expenditure Statistics by Condition

This section reports the estimated quality-adjusted price index and productivity index using the formulas from the previous section. Due to COVID–19's effect on population health and spending, we focus our estimates on the period 2000–2019.

We present an aggregate quality-adjusted price index that is a simplified version of Cutler et al. (2022). At an aggregate level, the analysis can be simplified as it avoids explicit allocation across conditions, where it may be challenging to match spending to health outcomes. For instance, suppose a patient dies with renal failure and heart disease, two serious conditions that often appear together. In this case, it is challenging to attribute this change in health across these conditions, as both likely contributed to the death. A similar allocation is necessary for spending across the two conditions. To address this issue, Cutler et al. (2022) uses a complex propensity score methodology that requires detailed micro data on conditions and

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places of service.

health outcomes. However, we can observe changes in aggregate health, which avoids the complexities of attribution, and is sufficient for aggregate measures of productivity.

Key inputs are shown in the top panel of Table 1. All inputs are deflated by the aggregate PCE index and all of the expenditure computations in Table 1 are lifetime computations from birth. The first row shows that the PCE health index grows faster than overall inflation by 0.45% per year. The condition-based price index grows considerably faster, as discussed previously, 1.4% per year faster than economy-wide inflation, consistent with Figure 2. The next three rows show the life expectancy for 2000 and 2019, along with the gain in life expectancy. Life expectancy increased by roughly 2 years during our sample period. The base period lifetime spending in 2000 is $512,877.[24] Multiplying the HCESC condition-based price index by the base period lifetime spending, we find that the hypothetical lifetime spending in 2019 to be $673,483, or an increase of $160,607 in lifetime spending for a population of similar health in 2019 relative to 2000.

Using this information, we form a variety of estimates to better gauge the value of medical care spending. We start with the naive but important benchmark scenario (1) where we assume all of the life expectancy change may be attributable to the health care sector. Scenario (1) on the bottom panel of Table 1 also ignores disability and assumes that the QALY gains equal the life expectancy change. In this scenario, spending change per year of life expectancy gained equals $80,303, because life expectancy rose by 2 years and spending by $160,607. For a $VQALY of $100,000 this implies an annual quality-adjusted price decline of 0.42%, relative to economy-wide inflation.[25] Using $VQALY from $150k or $250k, which is a range more consistent with recent estimates from Kearsley (2024), we find the price index falling substantially faster from about 1.66% to 5.55% per year.

In the next row (scenario 2), we reduce the growth in quality-adjusted life expectancy, reflecting the fact that the additional life years that individuals gain may be in less than perfect health. We follow Cutler et al. (2022) who find QALY gains that are 30% less than the life expectancy gains over the period of study. This adjustment reduces the value of medical care spending substantially. With a VSLY of $100k, we find that quality-adjusted prices rise by 0.21% annually, rather than fall by 0.42% as seen in scenario (1).

Finally, in the last two rows, we assume that the underlying health of the population has worsened for nonmedical reasons, implying the observed change in health due to medical care is understated. This assumption is consistent with trends in underlying population health in the U.S. Due to rising obesity rates and drug abuse (see Mokdad et al. (2024)), it may be argued that the underlying population health has declined over time due to nonmedical factors. For the 65+ population, Cutler et al. (2022) decompose how much of the change in health is due to medical and nonmedical factors. Over the period from 1999

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[24] This is computed using estimates of spending per capita by age from CMS combined with life expectancy tables for the year 2000 from the Center for Disease Control National Vital Statistics Report. In principle one could construct this again in 2019, but an advantage of the HCESC is that it holds the prevalence of conditions fixed across time, essentially holding the health of the population constant.

[25]

$$\begin{aligned} P &= \frac{S_t}{S_0} - \frac{\$VQALY \Delta H_t}{S_0} \\ &= \frac{\$673,483}{\$512,877} - \frac{\$100,000 \cdot (2Years)}{\$512,877} \\ &= 0.92 \end{aligned}$$

The value 0.92 is the index value over the entire time period. Annualized over the 19 years, the value is 0.9958, so the annualized price change is -0.42%.

to 2012, they find that the gains in health due to medical care are larger than gains in health generally, as obesity, among other factors, has reduced health. Because of this, they find changes in quality-adjusted life expectancy understate the impact of medical care by about 60% for the 65 and over population. Given that we are analyzing spending and outcomes at birth, this estimate from Cutler et al. (1998) may not apply directly. Therefore, we analyze a range of estimates. In the last two scenarios (3 and 4) we assume gains in health from medical care are understated by 30% or 60%, relative to scenario 2. We choose 30% as our preferred estimate, in addition to 60%, as we are analyzing a younger, potentially healthier population. Based on these adjustments, the central estimates show the quality-adjusted price index falling for most scenarios. Interestingly, across all four scenarios the quality-adjusted price index falls below the PCE health price index growth of 0.45% per year over this period, implying a potential bias in the official price measure in the sector across the range of scenarios. The bias is the difference between the current PCE health price index and the quality-adjusted price index. For example, for our preferred scenario (3) assuming the VSLY of $150k, correcting for the bias would decrease the price index by 1.74% (=0.45% - (-1.29%)) per year. As the price indexes are sensitive to the VSLY, the last column reports the change in spending per life year saved as a measure of the growth in expenditures per quality improvement. In all scenarios, the spending per QALY increase is over $70,000, which may be of interest to policymakers considering the opportunity costs of these expenditures.

Table 1. Quality-Adjusted Price Changes Based on Health Care Expenditure Statistics by Condition

Inputs into Quality-Adjusted Price Index

Description	Value
PCE Health Price Index Annual Growth	0.45%
Condition-based Price Index Annual Growth	1.4%
Life expectancy 2000	76.8
Life expectancy 2019	78.8
Life expectancy gain in year (2000-2019)	2.0
Est. Lifetime Spending in 2000	$512,877
Hypothetical Risk-Adjusted Lifetime Spending in 2019	$673,483
Change in Lifetime Spending 2000 to 2019	$160,607

Annual Quality-Adjusted Price Index Change

Scenario	Chg. QALY	Price Chg. VSLY 100,000	Price Chg. VSLY 150,000	Price Chg. VSLY 250,000	Chg. in Spending Per Chg. QALY
(1) Life expectancy equals QALY (baseline)	2.0	-0.42%	-1.66%	-5.55%	$80,303
(2) QALY ((1) $\downarrow 30\%$)	1.4	0.21%	-0.53%	-2.40%	$114,719
(3) Worsening population health (Scenario (2) $\uparrow 30\%$)	1.8	-0.22%	-1.29%	-4.39%	$88,245
(4) Worsening population health (Scenario (2) $\uparrow 60\%$)	2.2	-0.69%	-2.18%	-7.63%	$71,669

Notes: This table provides estimates of the quality-adjusted price index change for health care, relative to the economy-wide inflation. Economy wide inflation is measured using the aggregate BEA PCE price index. The top part of the table provides the key elements used in the price index calculation that are on the bottom of the table. The elements of the table are described in detail in the text.

To check whether our approximation methodology provides plausible estimates, we compare our results to the much more in-depth estimates from Cutler et al. (2022). One important difference between our papers is that Cutler et al. (2022) focuses solely on the 65+ population, while all of our calculations in Table 1 are lifetime calculations from birth. To make our results comparable, we recalculate life expectancy at 65 and lifetime spending at 65 in 2000, using age specific death rates and health care spending.[26] The HCESC does not currently separate spending for those above or below 65, so we assume spending growth is similar for these two populations, which is an arguably strong assumption that we discuss below. After making these adjustments, the base period lifetime spending of a 65-year-old is $295,738, the change in lifetime spending

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[26] See the appendix for specific calculations for the over-65 age group.

is \$92,610, and the change in life expectancy is 1.7 years. This corresponds to a quality-adjusted price index decline of 2.09% in scenario 4, with a VSLY of \$100,000. With the same assumptions regarding the VSLY and the share of health improvements due to medical care, we apply our formula to estimates from Cutler et al. (2022) and find that the implied quality-adjusted price index falls by about 3.5% per year.[27] This is a bit lower than our estimates, but the over-65 population in the U.S. is insured by Medicare, which has regulated prices that grow less quickly over our study period. Private insurance is the most common insurance for those under age 65.[28] If we factor in the lower price growth in the Medicare population, which grows over 1 percentage point slower than private insurers, then our estimate matches closely to those of Cutler et al. (2022).[29]

There are large differences in the quality-adjusted price index for the full population analyzed in Table 1, relative to the 65 and older analyzed in Cutler et al. (2022). The reason for this large difference is that the health gains go primarily to those over 65, but the lifetime health spending is shared roughly evenly between the under- and over-65 populations, so it appears that the value of medical care spending for the over-65 population is quite high. More precisely, about 85% of the improvement in life expectancy is occurring for those older than 65, while about 53% of the spending growth occurs below 65. One possibility is that the increase in spending is much more effective for the over-65 population. However, we think that the more likely reason for this difference is that health is an investment good, as in Grossman (1972), so that the spending below age 65 leads to better health outcomes post-65, highlighting the potential importance of studying the dynamics of the full population.

These estimates have implications for productivity measurement. To understand the implications, we adjust existing productivity estimates for health care from BLS. Analogous to equation 4, we can write the BLS multifactor productivity index as:

$$ProductivityIndex_{0,t}^{BLS} = \frac{\frac{\frac{N_t \cdot S_t}{N_0 \cdot S_0}}{\text{Output Price Deflator}_{0,t}}}{\frac{N_t C_t^R}{N_0 C_0^R}} \tag{5}$$

where $N_t \cdot S_t$ is nominal output for health care in period t, $N_0 \cdot S_0$ is nominal output in period 0, and Output Price Deflator$_{0,t}$ is the BLS price deflator for health care. To account for the changes discussed above (e.g., quality adjustment and defining the output as the treatment of a condition), one could replace the BLS price deflator with our quality-adjusted price index by multiplying the productivity measure in equation 5 by $\frac{\text{Output Price Deflator}_{0,t}}{P_{0,t}}$.

The top panel of Table 2 shows the inputs to this calculation. The BLS multifactor productivity change for the sector is relatively flat, with an increase of just 0.16% per year. The output price deflator grows

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[27] Specifically, we use their estimate of the change in lifetime spending and QALYs from Table 5 of Cutler et al. (2022). We compute base period lifetime spending using our methodology (but for 1999, which is the beginning of their sample period), as they do not report this number. We adjust all their numbers to be in 2019 dollars, rather than 2010 dollars.

[28] Based on estimates from BLS for hospitals, prices for individuals with private insurance grew by about 4% per year, while prices for individuals with Medicare insurance grew 2.5% per year.

[29] Specifically, as an alternative we lower the disease-specific price by half the price difference between private and Medicare price growth (about 0.7 percentage points a year) to account for the slower growth of Medicare prices, and we find the associated quality-adjusted price falls by 3.5%. After these adjustments, the similarity between our estimates provides some evidence that our methodology to approximate a quality-adjusted price index is reasonable. Details of this calculation are shown in the appendix section 8.3.

by 0.24% per year relative to economy-wide inflation. Note that the BLS price measure we use is health care and social assistance (NAICS 62), which varies from the BEA measure of PCE health. This sector includes hospitals and ambulatory care, but unlike PCE health, it excludes pharmaceuticals and includes the category of social assistance.[30] These differences are among the reasons that the BLS price deflator grows slower, 0.24% versus 0.45%, relative to the PCE health price index.

Table 2 shows how this adjustment impacts productivity measures. In scenario (3), assuming a VSLY of $150,000, we calculate that the annual productivity growth is 1.69% from 2000 to 2019, about a ten-fold difference in productivity. This implies a bias of 1.53% (=1.69% - 0.16%) per year. One can see that with this adjustment, the productivity estimate mirrors the quality-adjusted price index change. For example, in scenario (4), assuming a VSLY of $100,000, our productivity estimate is 1.09% per year, which implies a bias of 0.93% (=1.09% - 0.16%) per year, or a seven-fold difference in productivity.

Table 2. Quality-Adjusted Productivity Changes Based on the Health Care Expenditure Statistics by Condition

Inputs into Productivity Index change

Description	Value
BLS Mult. Productivity Health & Social Ass.	0.16%
BLS Output Price Deflator Health & Social Ass.	0.24%

Annual Quality-Adjusted Productivity Change

Scenario	Prod. Chg. VSLY 100,000	Prod. Chg. VSLY 150,000	Prod. Chg. VSLY 250,000
(1) Life expectancy equals QALY (baseline)	0.82%	2.06%	5.95%
(2) QALY ((1) $\downarrow 30\%$)	0.19%	0.93%	2.80%
(3) Worsening population health ((2) $\uparrow 30\%$)	0.62%	1.69%	4.79%
(4) Worsening population health ((2) $\uparrow 60\%$)	1.09%	2.58%	8.03%

Notes: This table provides estimates of the quality-adjusted productivity change for health care. The elements of the table are described in detail in the text.

Limitations: While we view this approach as providing a useful estimate for a quality-adjusted price, there are some important limitations. Most importantly, the paper relies on external information on population health and assumptions regarding how much of the population health change is due to medical care or other factors. The recent work by Cutler et al. (2022) provides some guidance suggesting that population health in the U.S. has likely worsened in recent years. The increase in disease prevalence in the HCESC that is also indicative of worsening population health. Consistent with these estimates, Romley et al. (2020) examine eight health conditions around this time period and find a health status index that worsens for seven out of eight conditions studied. There are also challenges with measuring health improvements based on population life expectancy. For example, life expectancy measures may not capture more complex dynamics, such as treatments that only have effects on health several years into the future.

Another important limitation is that our approach does not address the issue of clinical risk factors, like high cholesterol or diabetes that can lead to more serious conditions, such as heart disease, that can lead to morbidity and death. If hypertension and high cholesterol increase in the population, this can lead to more heart disease cases. An important contribution of Cutler et al. (2022) is to develop an accounting system to reallocate spending and health changes from direct health conditions to risk factors like hypertension and

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[30] However, social assistance accounts for less than 10% of this category, so it primarily reflects productivity of the health sector.

high cholesterol. This more appropriately lines up spending and associated outcomes for each condition. Our analysis attempts to address this limitation by using health information from Cutler et al. (2022).

Another limitation of the analysis is its focus on aggregate estimates. We do not have health information at the condition level, which can be informative regarding the quality-adjusted prices and productivity of different treatments. More disaggregated information, by condition, geography, and demography, is necessary to better understand why productivity is changing. However, the benefit of our approach is that it can more quickly be applied to provide a more timely top-line measure. The estimate presented here is just an approximation, and more information is needed to improve the accuracy of these estimates. While comprehensive estimates are challenging due to the vast data required, Cutler et al. (2022) has demonstrated the feasibility for the over-65 population and the Institute of Health Metric and Evaluation also demonstrates the feasibility of producing comprehensive estimates by providing disease outcome information for 204 countries (Vos et al. (2020)).

6.2. Additional Evidence

A key limitation of the HCESC-based approach presented here and by Cutler et al. (2022) is that there may be numerous unobserved risk factors affecting the health of individuals with a particular condition. For instance, the health of a person with diabetes may be very different across individuals and over time, but individuals with a more severe case are often coded the same as someone with a less severe case. Detailed risk factors of the person may be difficult to account for using only population health data. There are a few complementary approaches that have been taken that generally support the findings presented here.

One approach is to produce estimates based on the expected quality from disease models, which use evidence in the clinical literature to predict health outputs based on information about health inputs and patient health (National Research Council, 2011). Cutler et al. (2022) introduces an alternative analysis using a disease model for cardiovascular treatment. This approach does not rely on population health outcomes and finds results consistent with the population-based approach for cardiovascular conditions. Eggleston et al. (2019) use disease models to examine the value of treatment for diabetes patients in four countries, and find the benefit of health improvement typically exceeds the cost.

Related to the disease model approach, Dunn et al. (2024) study 13 health conditions and use information on quality from the medical literature from the Tufts' Cost Effectiveness Analysis Registry (CEAR). Specifically, they combine quality information from clinical studies with actual spending and treatment information using micro claims data. Many of the 13 conditions studied have expensive treatments that are patent protected, and quality-adjusted prices rise over the study period, highlighting that quality-adjusted prices do not necessarily fall. However, they project that in the long run, when drugs lose patent protection, quality-adjusted prices fall substantially for 12 of the 13 conditions.[31] A potential advantage of the approach taken in these papers is that quality is not measured based on observed outcomes, it is based on the clinical

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[31] Similar to this study, Dunn et al. (2022) use available information from the medical literature to approximate a quality-adjusted price, but at a more aggregate level. Specifically, they use information on advances in medical technologies from cost-effectiveness literature, proxies for the diffusion of medical technology, and combine this with information on the cost of treatment by medical condition from the HCESC. They also find quality-adjusted prices declining, similar to the population-based discussed in this paper.

literature that provides a measure of predicted health outcome. A disadvantage of this approach is that it does not directly explain health outcomes observed in the population. Moreover, as Hall (2017) points out, it may be challenging to model every separate condition and associated outcome. See Hall (2017) and Sheiner and Cutler (2024) for more detailed discussions of other papers in this literature.

Focusing on acute health conditions is another approach to help address this issue, as the acute health event itself and associated diagnosis codes provide key information about patient health. Due to the severity of these conditions, the outcome and the spending soon after the event can more readily be attributed to the health sector. This literature typically finds quality-adjusted prices declining rapidly (Cutler et al. (1998) for heart attacks, Dauda et al. (2022) for heart attacks, pneumonia, and heart failure). Examining eight health conditions, Romley et al. (2020) finds evidence of broad productivity improvement.

7. Conclusion

Accurately measuring productivity in the health care sector is essential for understanding the value of medical care spending, informing policy, and interpreting national trends in economic statistics. Yet, traditional approaches fail to account for improvements in health outcomes and the substantial quality gains driven by medical innovation. This paper demonstrates how the HCESC from BEA can be combined with external data on health and life expectancy to produce quality-adjusted price indexes that better reflect changes in real output and productivity in the sector.

Our results, consistent with a growing body of literature, indicate that quality-adjusted prices for health care have declined relative to conventional price indexes, implying significant unmeasured productivity growth. The estimates presented here suggest that official statistics may understate real output growth in the health sector by roughly 1 percent per year or more, depending on the value placed on health gains and adjustments for underlying population health trends.

These findings carry important implications. First, failure to properly account for health improvements can distort measures of sectoral productivity and bias assessments of living standards over time. Second, understanding how much of rising health care spending translates into improved health is central to ongoing debates over health care efficiency, pricing, and innovation policy. Improving these estimates could have important policy implications, as areas where productivity is lagging may be identified so appropriate policy tools may be deployed. Finally, the framework presented here highlights the usefulness of condition-based health accounts and integration of health outcome data to support more accurate and actionable economic statistics.

While challenges remain, such as how to disentangle medical and nonmedical contributors to health outcomes, the methodology outlined in this paper provides a new approach for improving the measurement of the health care sector.

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8. Appendix

8.1. Price Index for Single Condition

The price index for a single condition follows the work of Sheiner and Malinovskaya (2016) and Dauda et al. (2022). The starting point for our quality-adjusted price index is the cost of living index (COLI) from Fisher and Shell (1972). Their COLI is written as:

$$COLI = \frac{e(p_1, U_0)}{e(p_0, U_0)} = \frac{e(p_0, U_0) - (e(p_0, U_0) - e(p_1, U_0))}{e(p_0, U_0)} = \frac{e(p_0, U_0) - CV}{e(p_0, U_0)} \tag{6}$$

where $e(\cdot)$ is the expenditure function, which is the minimum expenditure required to achieve a certain level of utility given a set of prices. The COLI measures the change in expenditure necessary to hold utility constant. The second term separates out $(e(p_1, U_0) - e(p_0, U_0))$, which is a measure of compensating variation (CV), which is the focus of our discussion below.

To generate the index, a measure of consumer welfare is needed. Following Cutler et al. (1998) we use utility theory to measure the compensating variation. Let the representative consumer's utility at time t be $U(H(m_t), x_t)$ where m_t is the medical care input, $H(m_t)$ is the medical care production function that translated medical care into health. The term x_t is a numeraire good with a price normalized to 1. The consumer has an income Y and is subject to a budget constraint $p_t m_t + x_t \leq Y$. In this example, we are assuming that the representative consumer has just one condition, and the amount spent on the condition is m_t, which captures the number of services (e.g., hospital visits, prescription drugs, and doctors visits) and p_t captures the price of each of those services. The CV is defined by the following equality:

$$U(H(m_t), Y - p_t m_t + CV) = U(H(m_0), Y - p_0 m_0) \tag{7}$$

The CV is the expenditures necessary for the consumer to be indifferent across the two periods. A first-order approximation at period 0 results in the following relationship:

$$CV = \frac{U_h H_m(m_t - m_0)}{U_x} - (p_t m_t - p_0 m_0) \tag{8}$$

There are a couple of points to note about this equation. Most notably, the CV is derived without any assumption of consumers optimally consuming health care. While the formula holds when consumers utility maximize, it is also robust to the presence of market distortions, which are prevalent in the health care sector.

We are interested specifically in the change in expenditure necessary for a consumer to be indifferent in their treatment across periods. As we are not modeling the individual goods and services selected for treatment, we take the total spending on the treatment to be $S_t = p_t m_t$, making the $CV = \frac{U_h}{U_x} H_m(m_t - m_0) - (S_t - S_0)$. The term U_h is the change in utility as health changes and U_x is the dollar value of the utility change, so $\frac{U_h}{U_x}$ is the value of incremental health. Empirically, this is often taken as the value of a statistical life year. The term $H_m(m_t - m_0)$ is the change in health due to medical care. Together the term $\frac{U_h}{U_x} H_m(m_t - m_0)$ captures the dollar value of the health change.

The price index aims to capture the health expenditure necessary to hold utility constant across periods. So we take base period health expenditures as the denominator, and the numerator is the base period expenditure minus the welfare change captured by the CV formula, as shown in equation (6). The price index for condition j is then:

$$P^j = \frac{S_0 - CV}{S_0} \tag{9}$$

$$= \frac{S_t - \frac{U_h H_m (m_t - m_0)}{U_x}}{S_0} \tag{10}$$

$$= \frac{S_t}{S_0} - \frac{\$VQALY \Delta H_t}{S_0} \tag{11}$$

This is the growth in expenditures necessary to keep utility constant with the quality change.

8.2. Aggregate Price Index

The quality-adjusted price index is formed using the same theoretical ideas of Cutler et al. (2022), but is simplified along a number of dimensions. In the previous appendix section, we derived the equations for a single period. In this section we derive the lifetime aggregate estimates. Most importantly, we focus solely on aggregate estimates, rather than disease-specific measures. To construct the quality-adjusted price, we let the economy consist of people that are identical other than their ages. Let h_t be an individual's health status, where the inverse of the health status is the mortality rate $1/h_t$, so that life expectancy is h_t. Let $u(c_t)$ be the utility from a single period, where c_t is the numeraire good of all nonmedical expenditures.

In this simplified environment, the representative persons lifetime utility is, $U_t(c_t, h_t) = h_t u(c_t)$ (see Hall and Jones (2007) and Becker et al. (2005) for a similar formulation). Let the period budget constraint be $Y = p_t \cdot m_t \cdot z_t + c_t$ where $p_t \cdot m_t \cdot z_t$ is the expenditure on health at time t with m_t being the quantity of care per condition, p_t being the price of care, and z_t being the number of conditions treated, which captures the health of the population at time t. We can think of z_t as capturing all nonmedical factors that affect health. Health is produced with a production function $h_t = f(m_t, z_t)$ where higher levels of medical care increase health, but a higher number of health conditions z_t reduces health ($f_m(m_t, z_t > 0$ and $f_z(m_t, z_t < 0)$. To construct the price index we imagine the representative person as aging within the same year, so that prices and health technology are held fixed within a year t.[32] We next ask the hypothetical question of how the representative individual's welfare would change if they faced the same technology and prices from another time period.

The compensating variation, CV, between two time periods forms the foundation of the price index. Following Cutler et al. (1998) we consider the compensating variation change in utility over two time periods that makes utility constant across periods.

$$U_1(c_1 + CV, h_1) = U_0(c_0, h_0)$$

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[32] Alternatively, one could imagine the population receiving marginal benefits and costs from health treatment, and those marginal benefits and costs at different ages adding up to the representative consumer within a time period. A similar counterfactual is applied when constructing a period life expectancy measure, using mortality rates of different ages within the same time period to measure life expectancy.

Importantly the compensating variation is intended to identify the welfare effects across periods for an *identical* population, so z_t is held constant. Substituting in the budget constraint and the health production function to compute CV between period 0 and period 1:

$$f(m_1, z_0) \cdot u_1(Y - p_1 \cdot m_1 \cdot z_0 - CV) = f(m_0, z_0) \cdot u_0(Y - p_0 \cdot m_0 \cdot z_0) \tag{12}$$

Taking a first order Taylor series approximation around period 0 utility we obtain.

$$\begin{aligned} & f_m(m_0, z_0) \cdot u_0 \cdot (m_1 - m_0) + f(m_0, z_0) u_c \cdot ((Y - p_1 \cdot m_1 \cdot z_0 - CV) - (Y - p_0 \cdot m_0 \cdot z_0)) \\ & = f_m(m_0, z_0) \cdot u_0 \cdot (m_1 - m_0) + f(m_0, z_0) \cdot u_c \cdot ((-p_1 \cdot m_1 \cdot z_0 - CV) + p_0 \cdot m_0 \cdot z_0)) = 0 \end{aligned} \tag{13}$$

Solving for lifetime compensating variation we have:

$$CV \cdot f(m_0, z_0) = \frac{u_0}{u_c} \cdot f_m(m_0, z_0) \cdot (m_1 - m_0) - f(m_0, z_0) \cdot (p_1 \cdot m_1 \cdot z_0 - p_0 \cdot m_0 \cdot z_0) \tag{14}$$

Explaining the elements of this equation, CV is the compensating variation for one period, but it is multiplied by life expectancy $f(m_0, z_0)$ together providing a measure of the lifetime welfare change $(CV \cdot f(m_0, z_0))$. The term $f_m(m_0, z_0)$ is the marginal change in health due to a change in medical care and $(m_1 - m_0)$ is the change in medical care, so the change in health due to medical care is captured by: $f_m(m_0, z_0) \cdot (m_1 - m_0)$. The term u_0 is the utility in the base period, and u_c is the maginal utility of consumption, so $\frac{u_0}{u_c}$ is the dollar value of additional units of utility.

Following Sheiner and Malinovskaya (2016) and Dauda et al. (2022) and parallel to the single index above, the base period of the index is the total expenditure on medical care in the base period, and the numerator is the welfare change from the base-period expenditure. The associated price index is then:

$$\begin{aligned} P &= \frac{f(m_0, z_0) \cdot (p_1 \cdot m_1 \cdot z_0) - \frac{u_0}{u_c} f_m(m_0, z_0) \cdot (m_1 - m_0)}{f(m_0, z_0) \cdot p_0 \cdot m_0 \cdot z_0} \\ &= \frac{p_1 \cdot m_1}{p_0 \cdot m_0} - \frac{\frac{u_0}{u_c} f_m(m_0, z_0) \cdot (m_1 - m_0)}{f(m_0, z_0) \cdot p_0 \cdot m_0 \cdot z_0} \end{aligned} \tag{15}$$

Note that lifetime health and the number of treatments $f(m_0, z_0 \cdot z_0)$ cancels in the first term of equation 15. Therefore the first term becomes an index for the growth in the price of treatment, $\frac{p_1 \cdot m_1}{p_0 \cdot m_0}$. We can change this to match the index for a single period, so the total spending on treatment is $S_1 = p_1 \cdot m_1$. This term is capturing the full price of treatment for a population whose health does not change over time. The denominator of the second term is health in the base period, $f(m_0, z_0)$, which is equal to life expectancy, multiplied by medical care expenditure in the base period.

In this framework, a natural empirical counterpart for the first term is the condition-based price index from the HCESC. By construction, the HCESC price index tracks the price of treatment, which holds fixed the number of conditions in the population. For instance, if obesity leads to more individuals with heart disease, this does not affect the price index in the HCESC.

To obtain the denominator for the second term empirically, we use estimates from life expectancy tables in the base period and estimates of annual spending by age to compute lifetime spending estimates. The term in the numerator, $\frac{u_0}{u_c}$, is the dollar value per year of life ($\$VSLY$) often taken from external studies, as discussed in more detail in the text.

A desirable estimate of $f_m(m_0, z_0) \cdot (m_1 - m_0)$ would be the change in life expectancy solely due to medical care factors, $f(m_1, z_0) - f(m_0, z_0)$. However, what we observe in the data is $f(m_1, z_1)$ and $f(m_0, z_0)$, where both medical and nonmedical health inputs change over time. We could approximate the change in life expectancy due to medical care from: $f(m_1, z_1) - f(m_0, z_0)$, but this would be incorrect if nonmedical factors z_t change over time. A decomposition of $f(m_1, z_1) - f(m_0, z_0)$ can be made by adding and subtracting $f(m_1, z_0)$ to obtain: $(f(m_1, z_0) - f(m_0, z_0)) + (f(m_1, z_1) - f(m_1, z_0))$. The first term in the decomposition is the change in life expectancy solely due to medical care. The second term is the life expectancy change solely due to nonmedical factors. This shows that to obtain the desirable health measure, $f(m_1, z_0) - f(m_0, z_0)$, we need to subtract the change in health unrelated to medical care $f(m_1, z_1) - f(m_1, z_0)$ from the overall change in health $f(m_1, z_1) - f(m_0, z_0)$. Ideally, the equation should also capture the effect of quality of life on utility, and not just life expectancy, which could be incorporated in the above equation on the change in health, $f(m_1, z_0) - f(m_0, z_0)$.

The formula can be simplified to more clearly explain the empirical counterpart:

$$\begin{aligned}
P &= \frac{p_1 \cdot m_1}{p_0 \cdot m_0} - \frac{\$VQALY \cdot (f(m_1, z_0) - f(m_0, z_0))}{f(m_0, z_0) \cdot p_0 \cdot m_0 \cdot z_0} \\
&= \frac{S_1}{S_0} - \frac{\$VQALY \cdot (f(m_1, z_0) - f(m_0, z_0))}{f(m_0, z_0) \cdot S_0 \cdot z_0} \\
&= 1 + \text{Growth in Price of Treatment} - \frac{\$VQALY \cdot (\Delta\text{Lifetime Health from Medical Care}))}{\text{Lifetime Spending}_0} \qquad (16)
\end{aligned}$$

The basic ideas in this formula are contained in several other research papers. In earlier work covering the time period from 1960 to 2000, Cutler et al. (2006) determined that much of the improvement in life expectancy was related to improved health habits and especially a reduction in smoking. The paper assumed that half of the life years gained during this period were due to nonmedical factors (i.e., $f(m_1, z_1) - f(m_1, z_0)$ accounted for half the improvement). In Cutler et al. (2022) the methodology tracks the health of the population as well as associated health outcomes. The detailed and thorough methodology applied in the paper allows them to assess the productivity of each condition. This detailed estimate is aggregated at a top-line level as they decompose how much of the health change is due to medical and nonmedical factors. Over the period from 1999 to 2012, they find that the health from nonmedical changes of the population *declined* indicating that $f(m_1, z_1) - f(m_1, z_0)$ is negative, arguably due to conditions arising from growing obesity in the U.S. population. This implies that the health due to treatment changes, $(f(m_1, z_0) - f(m_0, z_0))$, is larger than the observed change in health in the population: $f(m_1, z_1) - f(m_0, z_0)$. More precisely, the QALY gain was 1.0 in the population over the age of 65, but holding population health constant they find the QALY gains to be 1.7. One way to interpret this is that health in the population would have been 0.7 QALYs higher if the health in the population did not deteriorate.

8.3. Calculation Details

This section provides some additional detail regarding the calculations discussed in the main paper. To review the calculation of the quality-adjusted price change from Table 1, we step through the calculation for scenario (1). Following equation (16) we have,

$$\begin{aligned}
P &= \frac{S_1}{S_0} - \frac{\$VQALY \cdot (f(m_1, z_0) - f(m_0, z_0))}{f(m_0, z_0) \cdot S_0 \cdot z_0} \\
&= 1 + \text{Growth in Price of Treatment} - \frac{\$VQALY \cdot (\Delta\text{Lifetime Health from Medical Care})}{\text{Lifetime Spending}_0} \\
&= \frac{\$673,483}{\$512,877} - \frac{\$100,000 \cdot (2 \text{ Years})}{\$512,877} \\
&= 0.92
\end{aligned}$$

The value 0.92 is the index value over the entire time period. Annualized over the 19 years, the value is 0.9958, so the annualized price change is -0.42%. This is the value in the upper left of Table 1. Similar calculations are conducted for each of the other values in the table, but with different $VQALY and different estimates of the change in lifetime health.

For the over-65 populations, the values are not included in the table. The key information for the over-65 population is the life expectancy gain from 2000 to 2019, which is 1.7 years, but 1.9 QALYs based on scenario (4) assumptions. The estimated lifetime spending in 2000 for a 65-year-old is $295,738, and the hypothetical lifetime spending is $388,348 in 2019. For a VSLY set at $100,000 and using the formula from above, the annual quality-adjusted price decline is 2.09% on an annual basis. Here the calculation is

$$P = \frac{\$388,348}{\$295,738} - \frac{\$100,000 \cdot (1.55 Years)}{\$295,738} \tag{17}$$

$$= 0.669 \tag{18}$$

Annualized over 19 years leads to a -2.09% price change.

The private prices for hospitals from the U.S. Bureau of Labor Statistics producer price index from 1999 to 2012 (the time period studied by Cutler et al. (2022)) grew by 4.5 percent per year, while the Medicare prices grew by 3.1 percent per year. If we reduce the growth in the price of the disease treatment by 0.7 percent per year, which is half of this difference, then over the entire period spending growth would slow by about 14%.

$$\begin{aligned} P &= \frac{\$388,348}{\$295,738}/1.14 - \frac{\$100,000 \cdot (1.55 Years)}{\$295,738} \qquad (19) \\ &= 0.51 \qquad (20) \end{aligned}$$

The associated annual price change would be -3.5%.