How much has growth of 'reasonable and necessary' medical treatments reduced U.S. mortality?

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Abstract

Only treatments that have been designated as "reasonable and necessary" (R&N) for the diagnosis or treatment of an illness or injury are covered by the U.S. Medicare program. Between 1994 and 2019, the number of R&N treatments that had ever been developed more than doubled, from 1210 to 2845.

Using publicly available data, we investigate the effect of R&N treatment growth on the mortality of Americans during the period 1999-2019. We employ a difference-in-differences (disease by year) research design: we measure attributes (the number and mean vintage) of the R&N treatments for a disease that had ever been developed by or before a year, and analyze their correlation with several measures of mortality from that disease in that year.

Mortality is more strongly related to the mean vintage of R&N treatments ever established than it is to the number of R&N treatments ever established, but estimates based on the two alternative innovation measures are qualitatively similar.

Our estimates indicate that the number of years of potential life lost before ages 85, 75, and 65 from a disease is significantly inversely related to the mean vintage of R&N treatments associated with the disease that had ever been established 0-4 or 0-6 years earlier. Mean age at death from a disease is significantly positively related to the mean vintage of R&N treatments associated with the disease that had ever been established 2-8 years earlier.

We also assess the impact that R&N treatment growth had on the mortality of different demographic groups, defined by education or race. Premature (before age 75) mortality of all education groups (people with 0-11 years, 12 years, or 13+ years of education) was reduced by R&N treatment growth. Innovation may have increased the longevity of more educated people sooner than it increased the longevity of less educated people, perhaps because more educated people have earlier access to innovations, but innovation appears to have had similar long-run (after 7 or 8 years) effects on the longevity of the three education groups.

Premature (before ages 85, 75, and 65) mortality rates of Black Americans is not significantly related to the mean vintage of R&N treatments that had ever been established 0-8 years earlier, but their mean age at death is significantly positively related to the mean vintage of R&N treatments that had ever established 5-8 years earlier. Innovation may have increased the longevity of black people later than it increased the longevity of other racial groups, perhaps because black people had later access to innovations, but the long-run (after 5-8 years) effect of innovation on the longevity of black people appears to be similar to its effects on the longevity of other racial groups.

During the period 1999-2019, age-adjusted rates of premature (before ages 85, 75, and 65) mortality declined by about 20%. We cannot reject the null hypothesis that in the absence of R&N treatment growth, premature mortality rates would not have declined during the period 1999-2019. Some factors other than biomedical innovation (e.g., the decline in smoking rates and the increase in educational attainment) probably contributed to the decline in mortality. However, other factors (the increase in obesity and chronic condition prevalence) probably contributed to an increase in mortality.

I. Introduction

Policymakers and economists recognize that longevity growth (or mortality reduction) is a major component of human development, or economic growth, broadly defined. Longevity growth is one of the three components of the Human Development Index (HDI) published by the United Nations Development Programme (2025).[1] Nordhaus (2003) argued that "to a first approximation, the economic value of increases in longevity in the last hundred years is about as large as the value of measured growth in non-health goods and services."

Many leading economists believe that at least one component of economic growth—GDP growth—is primarily driven by technological progress, which is generated by R&D investment. Jones (2002) presented a model in which long-run growth is driven by the discovery (via research effort) of new ideas throughout the world. His model built upon a large collection of previous research, including Romer (1990), Grossman and Helpman (1991), and Aghion and Howitt (1992), as well as earlier contributions by Phelps (1966), Shell (1966), Nordhaus (1969), and Simon (1986). When it awarded the 2025 Nobel Prize in Economic Sciences to three economists, the Royal Swedish Academy of Sciences (2025) declared that "sustained economic growth occurs when new technologies replace old ones as part of the process known as creative destruction."

The health sector of the U.S. economy is more research-intensive than the overall economy. According to Research America (2025), medical and health R&D as a percent of U.S. health spending was 5.13% in 2018, while, according to the National Center for Science and Engineering Statistics (2025), the ratio of U.S. R&D to GDP was 2.92%.

In this study, we will investigate the effect of technological progress, as embodied in new medical services, supplies, and equipment, on another major component of U.S. economic growth during the period 1999-2019:[2] the longevity growth (or mortality reduction) of Americans. In addition to assessing the impact that those innovations had on the mortality of all Americans, we will assess the impact that they had on the mortality of different demographic

[1] The HDI is the geometric mean of normalized indices of three variables: life expectancy at birth, mean years of schooling, and gross national income per capita.

[2] 1999 is the first year in which the ICD-10-CM cause of death classification was used. To avoid the impact of the COVID-19 pandemic, our sample period ends in 2019. From 2010 to 2019, the age-adjusted mortality rate declined by 4.3%. From 2019 to 2021, the age-adjusted mortality rate increased by 23%. See Appendix Figure 1.

groups, defined by education or race. All of the data we will use are publicly available on the internet.

We will employ a difference-in-differences (disease by year) research design: we will construct several measures of the medical treatments (items and services) officially designated as 'reasonable and necessary' (R&N) to treat a disease that had ever been developed by or before a year,[3] and analyze their correlation with several measures of mortality from that disease in that year. Medicare coverage is limited to treatments that are reasonable and necessary for the diagnosis or treatment of an illness or injury (and within the scope of a Medicare benefit category).

As shown in Figure 1, between 1994 and 2019, the number of R&N treatments used to treat at least one disease that had ever been developed more than doubled, from 1210 to 2845. As illustrated by Figure 2, the magnitude of the increase varied considerably across diseases. From 1994 to 2019, the number of R&N treatments associated with "malignant neoplasms of other and unspecified sites within the lip, oral cavity and pharynx" (C03-C09, C14.2-C14.8) increased by 66%, from 172 to 285, while the number of R&N treatments associated with "infections with a predominately sexual mode of transmission: other and unspecified syphilis" (A50-A51, A52.7-A52.9, A53) increased by 132%, from 170 to 395. We will estimate econometric models to test the hypothesis that there were larger reductions in mortality from diseases for which there was more growth in R&N treatments.

In the next section, we discuss the measurement of R&N treatments, by disease and year. In section III, we present our econometric model of mortality. Data sources and descriptive statistics are presented in section IV. Empirical results are presented in section V. Implications of the estimates are discussed in section VI. The final section provides a summary.

II. Measurement of 'reasonable and necessary' (R&N) treatments

There are three ways in which an item or service can be covered by Medicare. First, it can be covered under a National Coverage Determination (NCD): a determination by the Centers for Medicare & Medicaid Services (CMS) that a particular item or service is covered nationally

[3] During the period 2010-2023, data on the number of R&N treatments actually provided by Medicare are available. During that period, growth in the number of R&N treatments actually provided is strongly positively correlated across diseases with growth in the number of R&N treatments that had ever been developed.

under Medicare. Second, it can be covered under a Local Coverage Determination (LCD): a determination by one or more Medicare Administrative Contractors (MACs) that a particular item or service is covered on a contractor-wide basis in accordance with the "reasonable and necessary" standard. LCDs may be developed in the absence of an NCD or as a supplement to an NCD, as long as the LCD policy does not conflict with national policy. Third, in the absence of an LCD or NCD, claims are reviewed on a claim-by-claim basis by the MACs. In such cases, the MACs review the claim on an individual basis to ensure that all CMS requirements have been met prior to paying the claim.

Due to data limitations, our measures of R&N treatments, by disease and year, will be based solely on treatments covered by LCDs. Our R&N treatment measures are therefore subject to measurement error, but according to CMS (2025a), "most Medicare coverage decisions are made locally by the MACs."[4] Moneer et al (2024) also noted that "local coverage determinations…represent the vast majority of Medicare's coverage decisions for new technologies."

Our measures will be based on a CMS database (the "Current and Retired Articles" component of the Medicare Coverage Database) of treatments that have been designated by MACs as 'reasonable and necessary' to treat a disease (Center for Medicare and Medicaid Services (2025b, 2025c)). This database contains 575,664 links between 3404 medical items and services and 7344 (narrowly defined) covered disease (ICD-10-CM) codes. As shown in Appendix Table 1, these medical items and services fall into many categories and subcategories, e.g., molecular testing, imaging, chemotherapy, and cardiovascular procedures. Medical items and services are defined by Healthcare Common Procedure Coding System (HCPCS) codes (see Gutmann (2024)). HCPCS was established in 1978 by the Federal government to standardize the reporting of medical services, supplies, and equipment, essentially creating a unified system for medical billing across different healthcare providers and payers. While initially voluntary, the Health Insurance Portability and Accountability Act (HIPAA) of 1996 made the use of HCPCS codes mandatory for all healthcare transactions. Appendix Table 2 provides an illustration of the data for a single disease, Salmonella sepsis (A02.1). Thirty-one HCPCS codes

[4] The number of treatments (HCPCS codes) covered by LCDs (3404) is more than ten times the number covered by NCDs (200-300). According to the Medicare Coverage Database (Centers for Medicare and Medicaid Services (2025b)), as of 21 December 2024, there were 338 NCDs and 2324 LCDs.

(listed in order of year of HCPCS code establishment) are covered in at least one LCD for that disease.

We will analyze the impacts of two attributes of the R&N treatments for each disease in each year: the *number* (or variety) of treatments, and the mean *vintage* (year of code establishment) of treatments. Numerous authors have provided both theoretical and empirical support for the hypothesis that increased product variety is an important source of economic growth. Dixit and Stiglitz (1977, p. 297) argued that "less variety…entails some welfare loss." Judd (1985) and Romer (1990) modeled growth based on horizontal product innovations, using the Dixit-Stiglitz model of product variety. Segerstrom et al (1990) noted that most of the product-life-cycle literature has treated product innovation as being the introduction of greater variety. Grossman and Helpman (1991, p. 53) treat "technology-based growth as a process of generating an ever-expanding *variety* of horizontally differentiated products" [emphasis added]. Their consumption index exhibits *love of variety* over an infinite set of horizontally differentiated products, as in Dixit and Stiglitz. Utilizing panel data for 19 OECD countries, Funke and Ruhwedel (2001) found that an index of relative product variety was significantly positively correlated across countries with relative per capita income levels.

There is also theoretical and empirical support for the hypothesis that the *vintage* of technology or capital has a positive effect on economic growth. As noted by Jovanovic and Yatsenko (2012), in "the Spence–Dixit–Stiglitz tradition…new goods [are] of higher quality than old goods." In 1987, when the Royal Swedish Academy of Sciences (1987) awarded the Nobel Prize in Economic Sciences to Robert Solow for his contributions to the theory of economic growth, it noted that "the most important aspect of Solow's article was not so much the empirical outcome, but the method of analyzing 'vintage capital'."

III. Econometric model of mortality

Our assessment of the impact that R&N treatments had on the mortality of Americans will be based on the following two-way fixed effects model:

$$\ln(\text{mortality}_{dt}) = \beta_k \, \text{r\&n_measure}_{d,t-k} + \alpha_d + \delta_t + \varepsilon_{dt} \qquad (1)$$

where mortality_{dt} is one of the following variables:

$ypll85_{dt}$ = the number of years of potential life lost before age 85 due to disease d in year t (t = 1999, 2000, 2001,…, 2019)

$ypll75_{dt}$ = the number of years of potential life lost before age 75 due to disease d in year t

$ypll65_{dt}$ = the number of years of potential life lost before age 65 due to disease d in year t[5]

age_death_{dt} = the mean age at death from disease d in year t

n_deaths_{dt} = the number of deaths from disease d in year t

and $r\&n_measure_{d,t-k}$ is one of the following variables:

$\ln(n_r\&n_{d,t-k})$ = the log of the number of R&N treatments for disease d whose codes were established by year t-k (k = 0, 1, 2,…, 8)

$vint_r\&n_{d,t-k}$ = the mean vintage (year of code establishment) of R&N treatments for disease d whose codes were established by year t-k

$n_r\&n_{d,t-k}$ is calculated as follows:

$n_r\&n_{d,t-k} = \sum_h covered_{hd}\ established_{h,t-k}$

where

$covered_{hd}$ = 1 if HCPCS code h is covered for disease d in at least 1 LCD
= 0 if HCPCS code h is not covered for disease d in at least 1 LCD

$established_{h,t-k}$ = 1 if HCPCS code h was established by year t-k
= 0 if HCPCS code h was not established by year t-k

$vint_r\&n_{d,t-k}$ is calculated as follows:

$vint_r\&n_{d,t-k} = (\sum_h covered_{hd}\ established_{h,t-k}\ hcpcs_year_h) / (\sum_h covered_{hd}\ established_{h,t-k})$

where

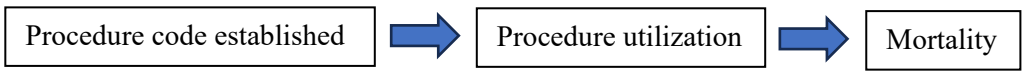
[5] The U.S. CDC's WISQARS Years of Potential Life Lost (YPLL) Report website permits one to specify age thresholds of 65, 70, 75, 80, and 85. The World Health Organization has used YPLL to measure disease burden in its Global Burden of Disease (GBD) and Global Health Estimates (GHE) reports for many years. In the 2010 GBD, the WHO used an age threshold of 86.01 years for all persons. In the current GHE, the WHO uses an age threshold of 91.93 years for all persons.

$hcpcs_year_h$ = the year in which HCPCS code h was established

In eq. (1), α_d is a fixed effect for disease d, and δ_t is a fixed effect for year t. The year fixed effects (δ_t's) in eq. (1) control for the effects of changes in aggregate demographic and macroeconomic variables (e.g. population size and age structure, GDP, educational attainment), to the extent that those variables have similar effects on mortality from different diseases.

Eq. (1) will be estimated by weighted least-squares. When $mortality_{dt} \neq age_death_{dt}$, the weight will be $\sum_t mortality_{dt}$. When $mortality_{dt} = age_death_{dt}$, the weight will be n_deaths_{dt}. Disturbances will be clustered within diseases.

Eq. (1) allows the effect on mortality of the number or vintage of R&N treatments ever established to be subject to a lag. There may be a lag for two reasons, which may be depicted as follows:



First, peak utilization of a procedure may occur years after the code for the procedure was established. We can obtain some evidence about the shape of the typical procedure "age-utilization profile"—the relationship between time since procedure code establishment and procedure utilization—using annual 2013-2022 CMS data (Center for Medicare and Medicaid Services (2025d)). Appendix Figure 2 shows the mean number of times each procedure was used, by age (number of years after code establishment) of procedure. Surprisingly, mean utilization of procedures is about half a million in the year that the code was established (and in each of the following 2 years). It rises to 700,000 by age 5 and then starts to decline.

A potential explanation for this is that the establishment of a HCPCS code may be a "lagging indicator": procedures may be used years before they are assigned HCPCS codes. For one important type of procedure—provider-administered drugs—we have evidence to support this hypothesis. Medicare contractors (e.g., Palmetto GBA (2025)) publish "NDC/HCPCS Crosswalks": listings of each National Drug Code (NDC) that is assigned to a HCPCS. From the Medical Expenditure Panel Survey (MEPS) Prescribed Medicine Files (Agency for Healthcare Research and Quality (2025)), we can obtain estimates of the number of prescriptions by NDC and year during the period 1996-2022. Our calculations reveal that 16% of MEPS prescriptions for NDCs linked to HCPCS codes were consumed in years prior to the year the HCPCS code

was established. This provides support for the hypothesis that procedures may be used years before they are assigned HCPCS codes.

The diseases identified in the LCDs are extremely detailed; 7344 distinct diseases are identified. The diseases identified in the mortality data are less detailed; 3914 distinct ICD-10-CM causes of death are identified in the 2019 mortality data. We will use the CDC's 358 cause of death classification (Centers for Disease Control and Prevention (2025a; page 24)) to aggregate the data and perform the analysis. External causes of mortality (*U01-*U03, V01-Y89) are excluded.

IV. Data sources

R&N treatment data. Data on $covered_{hd}$ (which indicates whether HCPCS code h is covered for disease d in at least 1 local coverage determination) were obtained from CMS' Current and Retired Articles database, which contains data on the most current, in effect (or future effective), and retired, Local Coverage Article versions. Data on $hcpcs_year_h$ (the year in which HCPCS code h was established) were obtained from the Restructured BETOS Classification System database (Center for Medicare and Medicaid Services (2025e)). Data on the number of services and Medicare expenditure, by HCPCS code and year (2013-2022), were obtained from the Medicare Physician & Other Practitioners - by Geography and Service database (Center for Medicare and Medicaid Services (2025d)).

Mortality Data were obtained from annual 1999-2019 Multiple Cause-of-Death Mortality files derived from the National Vital Statistics System of the National Center for Health Statistics. These files may be downloaded from the National Bureau of Economic Research (2025) website. Each record in the microdata is based on information abstracted from death certificates filed in vital statistics offices of each State and District of Columbia. Causes of death were coded according to the International Classification of Diseases, Tenth Revision from 1999 on. Each record contains the 358-cause recode of the underlying cause of death, the decedent's age at time of death, educational attainment, and race.

Appendix Table 3 displays 1999 and 2019 mortality and R&N treatment data for the top 38 diseases, ranked by number of deaths during 1999-2019.

V. Empirical results

Estimates of eq. (1) when $r\&n_measure_{d,t-k} = \ln(n_r\&n_{d,t-k})$ for different mortality measures are reported in Appendix Table 4. Estimates of eq. (1) when $r\&n_measure_{d,t-k} = vint_r\&n_{d,t-k}$ for different mortality measures are reported in Table 1 and plotted in Figure 3. The estimates based on the two alternative innovation measures are qualitatively similar, but mortality is more strongly related to the mean vintage of R&N treatments ever established than it is to the number of R&N treatments ever established, so henceforth we will focus on estimates of eq. (1) when $r\&n_measure_{d,t-k} = vint_r\&n_{d,t-k}$.

In panel A of Table 1 and Figure 3, the dependent variable is $\ln(ypll85_{dt})$: the log of the number of years of potential life lost before age 85 due to disease d in year t. $\ln(ypll85_{dt})$ is significantly inversely related to the mean vintage of R&N treatments ever established 0 to 4 years earlier. It is most strongly inversely related to the mean vintage of R&N treatments ever established one year earlier. The point estimate of β_1 indicates that a one-year increase in R&N treatment vintage reduced premature (before age 85) mortality one year later by 1.4%. Between 1999 and 2019, the weighted (by $ypll85_{dt}$) mean value of $vint_r\&n_{d,t-1}$ increased by 10.6 years (from 1987.4 to 1998.0). This implies that the 1998-2018 increase in vintage reduced premature (before age 85) mortality by 14.6% (= .0138 * 10.6). During the period 1999-2019, the age-adjusted rate of the number of years of potential life lost before age 85 per 100,000 population declined by about 20%.

In panel B of Table 1 and Figure 3, the dependent variable is $\ln(ypll75_{dt})$: the log of the number of years of potential life lost before age 75 due to disease d in year t. $\ln(ypll75_{dt})$ is significantly inversely related to the mean vintage of R&N treatments ever established 0 to 6 years earlier. It is most strongly inversely related to the mean vintage of R&N treatments ever established three years earlier. The point estimate of β_3 indicates that a one-year increase in R&N treatment vintage reduced premature (before age 75) mortality three years later by 1.7%.

In panel C of Table 1 and Figure 3, the dependent variable is $\ln(ypll65_{dt})$: the log of the number of years of potential life lost before age 65 due to disease d in year t. $\ln(ypll65_{dt})$ is significantly inversely related to the mean vintage of R&N treatments ever established 0 to 6 years earlier. It is most strongly inversely related to the mean vintage of R&N treatments ever

established three years earlier. The point estimate of β_3 indicates that a one-year increase in R&N treatment vintage reduced premature (before age 65) mortality three years later by 1.8%.

In panel D of Table 1 and Figure 3, the dependent variable is $\ln(age_death_{dt})$: the log of the mean age at death from disease d in year t. $\ln(age_death_{dt})$ is significantly positively related to the mean vintage of R&N treatments ever established 2 to 8 years earlier. It is most strongly related to the mean vintage of R&N treatments ever established five years earlier. The point estimate of β_5 indicates that a one-year increase in R&N treatment vintage increased mean age at death five years later by 0.23%. During the period 1999-2019, mean age at death increased by 1.38%.

In panel E of Table 1, the dependent variable is $\ln(n_deaths_{dt})$: the log of the number of deaths from disease d in year t. $\ln(n_deaths_{dt})$ is not significantly related to the mean vintage of R&N treatments ever established in year t or any of the previous 8 years. The innovation-induced reductions in the number of years of potential life lost before ages 85, 75, and 65 appear to be due to an increase in mean age at death from the disease rather than to a reduction in the number of deaths from the disease.

As noted above, we can assess the impact that innovation had on the mortality of different demographic groups, defined by education or race, by estimating eq. (1) using group-specific mortality data. Estimates of eq. (1) when $r\&n_measure_{d,t-k} = vint_r\&n_{d,t-k}$, by educational attainment of the decedent, are shown in Appendix Table 5 and plotted in Figure 4. Educational attainment is divided into three categories: 0-11 years, 12 years, and 13+ years of education. The left side of Appendix Table 5 (panels A, B, and C), and the top of Figure 4 (panel A), show the estimates when $mortality_{dt} = ypll75_{dt}$. For all three education groups, $\ln(ypll75_{dt})$ is significantly inversely related to the mean vintage of R&N treatments ever established 0 to 5 years earlier. This indicates that premature (before age 75) mortality of all education groups was reduced by medical innovation. Surprisingly, medical innovation appears to have had a larger (more negative) impact on the mortality of people with 12 years of education than it had on the mortality of people with either less or more education, although the estimated differences may not be statistically significant.

The right side of Appendix Table 5 (panels D, E, and F), and the bottom of Figure 4 (panel B), show the estimates by education group when $mortality_{dt} = age_death_{dt}$. Mean age at death of people with 12 or 13+ years of education is significantly positively related to the mean

vintage of R&N treatments ever established 0-8 years earlier, but mean age at death of people with 0-11 years of education is only significantly positively related to the mean vintage of R&N treatments ever established 7-8 years earlier. This may indicate that innovation increased the longevity of more educated people sooner than it increased the longevity of less educated people, perhaps because more educated people had earlier access to innovations. However, innovation appears to have similar had long-run (after 7 or 8 years) effects on the longevity of the three education groups.

To assess whether innovation had different effects on the mortality of different racial groups, we also estimated eq. (1) using only black mortality data. These estimates are shown in Appendix Table 6. $vint_r\&n_{d,t-k}$ did not have a significant effect on any of the three premature mortality measures ($\ln(ypll85_{dt})$, $\ln(ypll75_{dt})$, $\ln(ypll65_{dt})$) for any value of k. The standard errors of the estimates in Table 1 and Appendix Table 6 are quite similar, so the insignificance of the estimates in Panels A, B, and C of Appendix Table 6 does not appear to be due to greater volatility of the black mortality data. Mean age at death of blacks is significantly positively related to the mean vintage of R&N treatments ever established 5-8 years earlier. The estimates may indicate that innovation increased the longevity of black people later than it increased the longevity of other racial groups, perhaps because black people had later access to innovations. However, the long-run (after 5-8 years) effect of innovation on the longevity of black people appears to be similar to its effects on the longevity of other racial groups.

VI. Discussion

Estimates of two versions of eq. (1)—including and excluding $r\&n_measure_{d,t-k}$ as a regressor—enable us to estimate how much biomedical innovation reduced mortality during the period 1999-2019. When $r\&n_measure_{d,t-k}$ is included in eq. (1), δ_{2019} is an estimate of the 1999-2019 change in mortality, holding constant $r\&n_measure_{d,t-k}$, i.e., in the *absence* of biomedical innovation. (δ_{1999} is normalized to zero.) When $r\&n_measure_{d,t-k}$ is excluded from eq. (1), δ_{2019} is an estimate of the 1999-2019 change in mortality in the *presence* of biomedical innovation. Changes in age-adjusted mortality *rates* can be computed by subtracting the corresponding log-change in age-adjusted population from the δ_{2019} estimates.

These calculations are shown for four mortality measures (when $r\&n_measure_{d,t-k}$ = $vint_r\&n_{d,t-k}$) in Figure 5. In each case, we use the lag for which the relationship is most significant. Panel A shows estimates of the post-1999 log change in the age-adjusted ypll85 rate in the presence and absence of the change in vint_r&n one year earlier. The growth (log-change) in the presence of biomedical innovation is -0.20 and is significantly different from zero. The growth in the absence of biomedical innovation is -0.05 and is not significantly different from zero. We cannot reject the null hypothesis that in the absence of biomedical innovation, as measured by the lagged change in vint_r&n, the age-adjusted ypll85 rate would not have declined during the period 1999-2019. The estimates for the age-adjusted ypll75 and ypll65 rates in Panels B and C are quite similar. As shown in Panel D, mean age at death was 0.98% higher in 2019 than it was in 1999 (controlling for disease fixed effects), and this increase was statistically significant. Our estimates indicate that, if vint_r&n had not increased between 1994 and 2014, mean age at death would have been 1.23% *lower* in 2019 than it was in 1999, although this estimated decline is not statistically significantly different from zero.

Some factors other than biomedical innovation probably contributed to the decline in mortality. The adult cigarette smoking rate declined from 23.5% in 1999 to 13.7% in 2018 (American Lung Association (2025)). The fraction of adults who had at least a bachelor's degree increased from 23.9% in 1997 to 34.2% in 2017 (American Council on Education (2025)). However, other factors probably contributed to an increase in mortality. From 1999-2000 through 2017-March 2020, US obesity prevalence increased from 30.5% to 41.9%, and the prevalence of severe obesity increased from 4.7% to 9.2%. Obesity-related conditions include heart disease, stroke, type 2 diabetes and certain types of cancer. These are among the leading causes of preventable, premature death (Centers for Disease Control and Prevention (2025b)). And between 2007 and 2018, the prevalence of 14 out of 21 chronic conditions among male Medicare beneficiaries increased, and the prevalence of 16 out of 21 chronic conditions among female beneficiaries increased (Center for Medicare and Medicaid Services (2025f)).

VII. Summary and conclusions

Only treatments that have been designated as "reasonable and necessary" (R&N) for the diagnosis or treatment of an illness or injury are covered by the U.S. Medicare program. Between 1994 and 2019, the number of R&N treatments that had ever been developed more than doubled, from 1210 to 2845.

Using publicly available data, we investigated the effect of R&N treatment growth on the mortality of Americans during the period 1999-2019. We employed a difference-in-differences (disease by year) research design: we measured attributes (the number and mean vintage) of the R&N treatments for a disease that had ever been developed by or before a year, and analyzed their correlation with several measures of mortality from that disease in that year.

Mortality is more strongly related to the mean vintage of R&N treatments ever established than it is to the number of R&N treatments ever established, but estimates based on the two alternative innovation measures are qualitatively similar.

Our estimates indicated that the number of years of potential life lost before ages 85, 75, and 65 from a disease is significantly inversely related to the mean vintage of R&N treatments associated with the disease that had ever been established 0-4 or 0-6 years earlier. Mean age at death from a disease is significantly positively related to the mean vintage of R&N treatments associated with the disease that had ever been established 2-8 years earlier.

We also assessed the impact that R&N treatment growth had on the mortality of different demographic groups, defined by education or race. Premature (before age 75) mortality of all education groups (people with 0-11 years, 12 years, or 13+ years of education) was reduced by R&N treatment growth. Innovation may have increased the longevity of more educated people sooner than it increased the longevity of less educated people, perhaps because more educated people have earlier access to innovations, but innovation appears to have had similar long-run (after 7 or 8 years) effects on the longevity of the three education groups.

Premature (before ages 85, 75, and 65) mortality rates of Black Americans is not significantly related to the mean vintage of R&N treatments that had ever been established 0-8 years earlier, but their mean age at death is significantly positively related to the mean vintage of R&N treatments that had ever established 5-8 years earlier. Innovation may have increased the longevity of black people later than it increased the longevity of other racial groups, perhaps because black people had later

access to innovations, but the long-run (after 5-8 years) effect of innovation on the longevity of black people appears to be similar to its effects on the longevity of other racial groups.

During the period 1999-2019, age-adjusted rates of premature (before ages 85, 75, and 65) mortality declined by about 20%. We cannot reject the null hypothesis that in the absence of R&N treatment growth, premature mortality rates would not have declined during the period 1999-2019. Some factors other than biomedical innovation (e.g., the decline in smoking rates and the increase in educational attainment) probably contributed to the decline in mortality. However, other factors (the increase in obesity and chronic condition prevalence) probably contributed to an increase in mortality.

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Figure 1
Number of codes for R&N treatments ever established, all diseases, 1994-2019

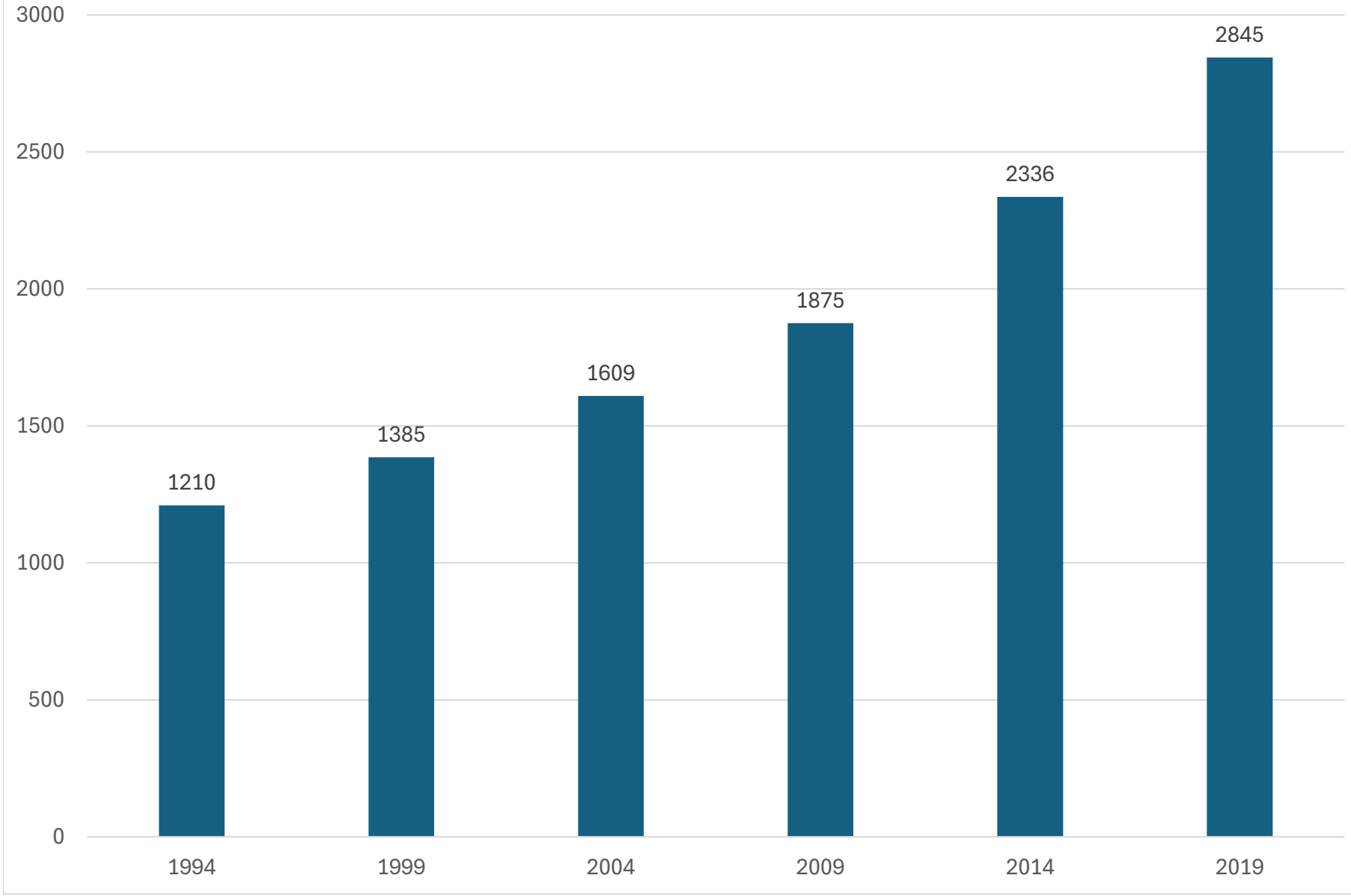


Figure 2

Number of codes for R&N treatments associated with five diseases ever established, 1994-2019

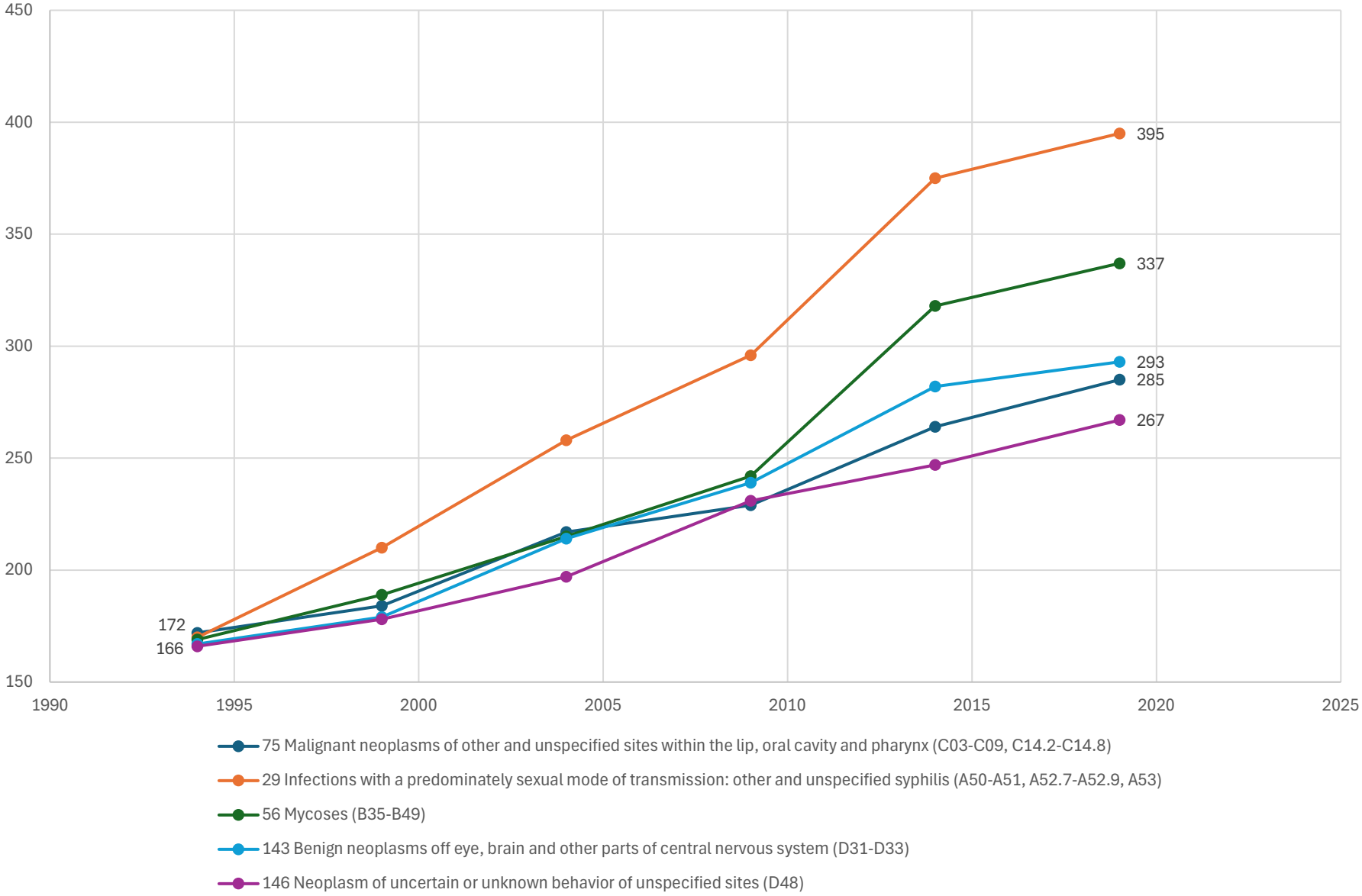
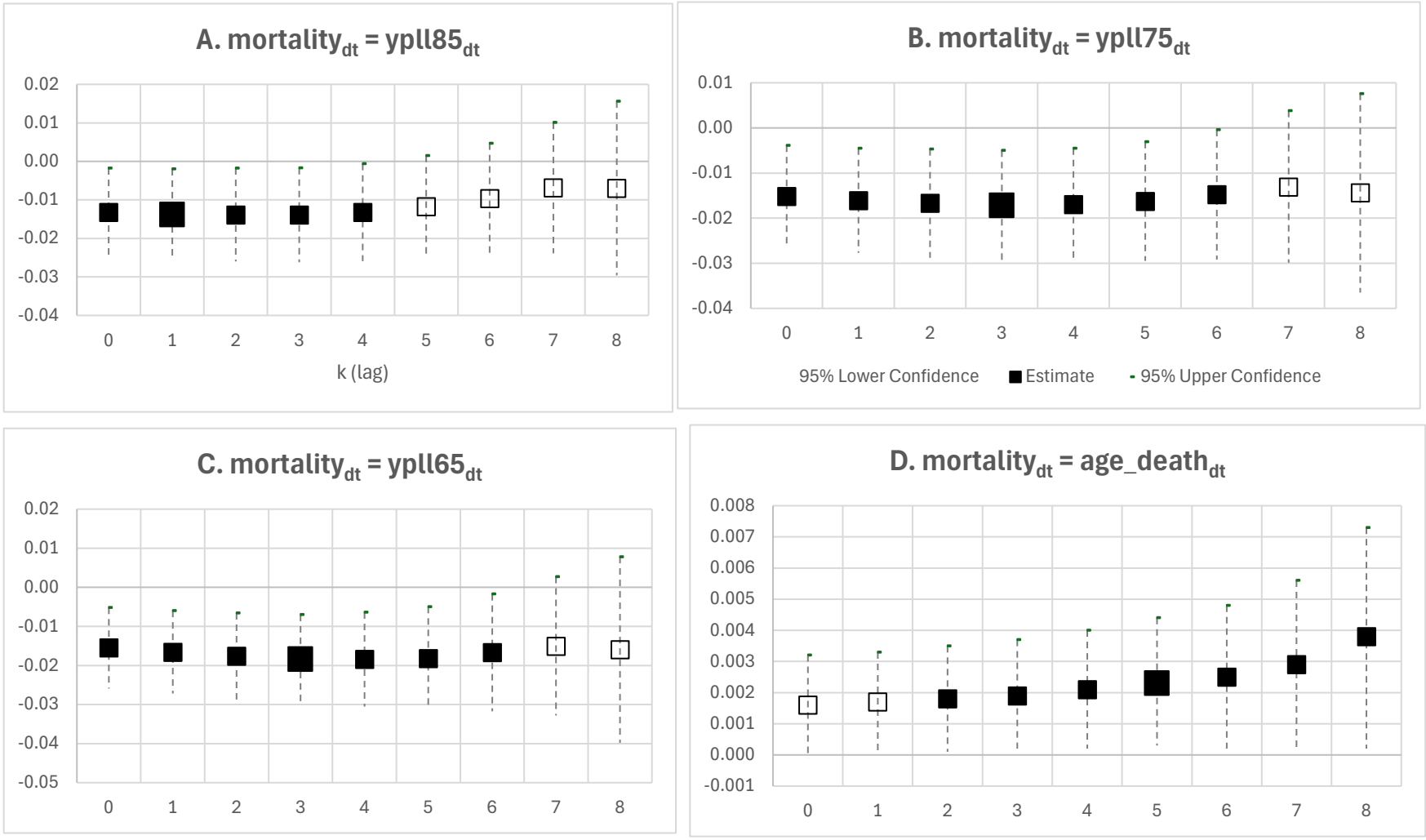


Figure 3

Estimates of β_k from model $\ln(mortality_{dt}) = \beta_k \, vint_r\&n_{d,t-k} + \alpha_d + \delta_t + \varepsilon_{dt}$



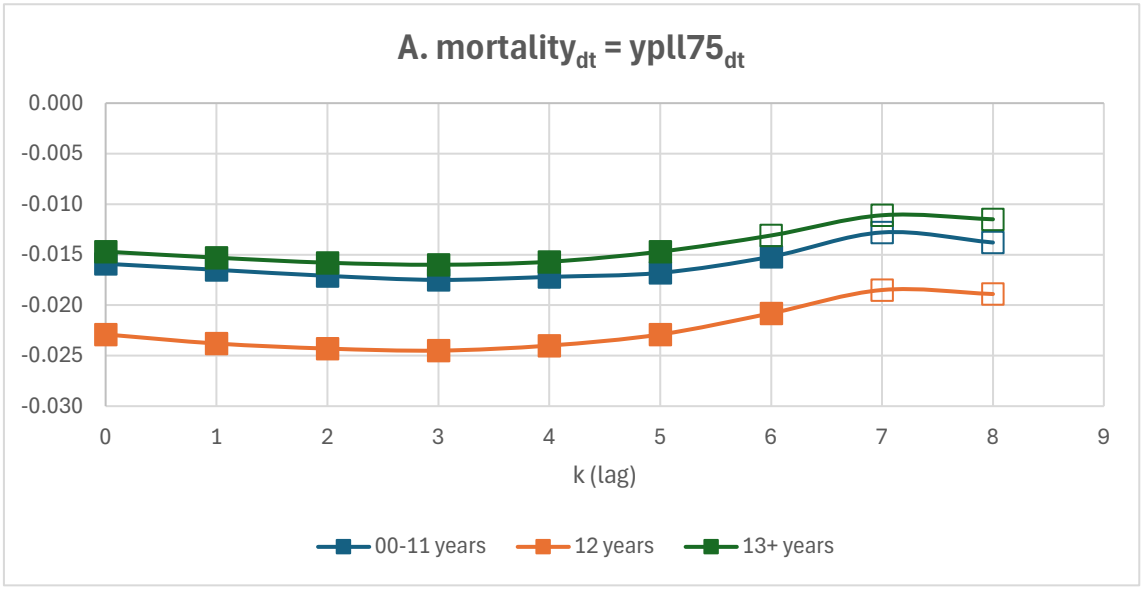
A solid marker indicates a statistically significant (p-value < .05) estimate.

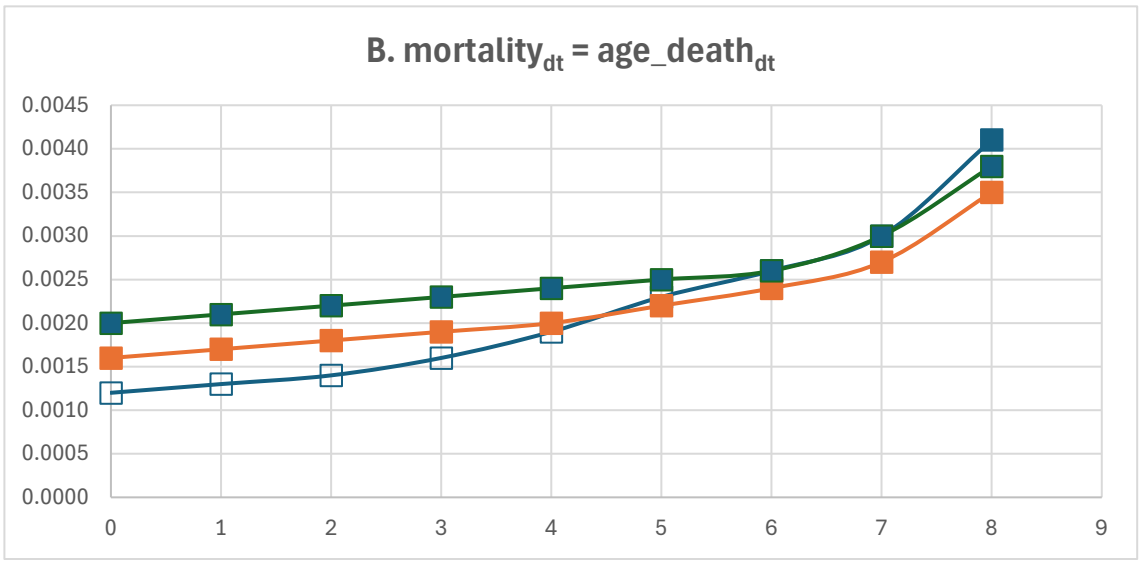
A hollow marker indicates a statistically insignificant estimate.

Figure 4

MORTALITY BY EDUCATIONAL ATTAINMENT

Estimates of β_k from model $\ln(mortality_{dt}) = \beta_k\ vint_r\&n_{d,t-k} + \alpha_d + \delta_t + \varepsilon_{dt}$

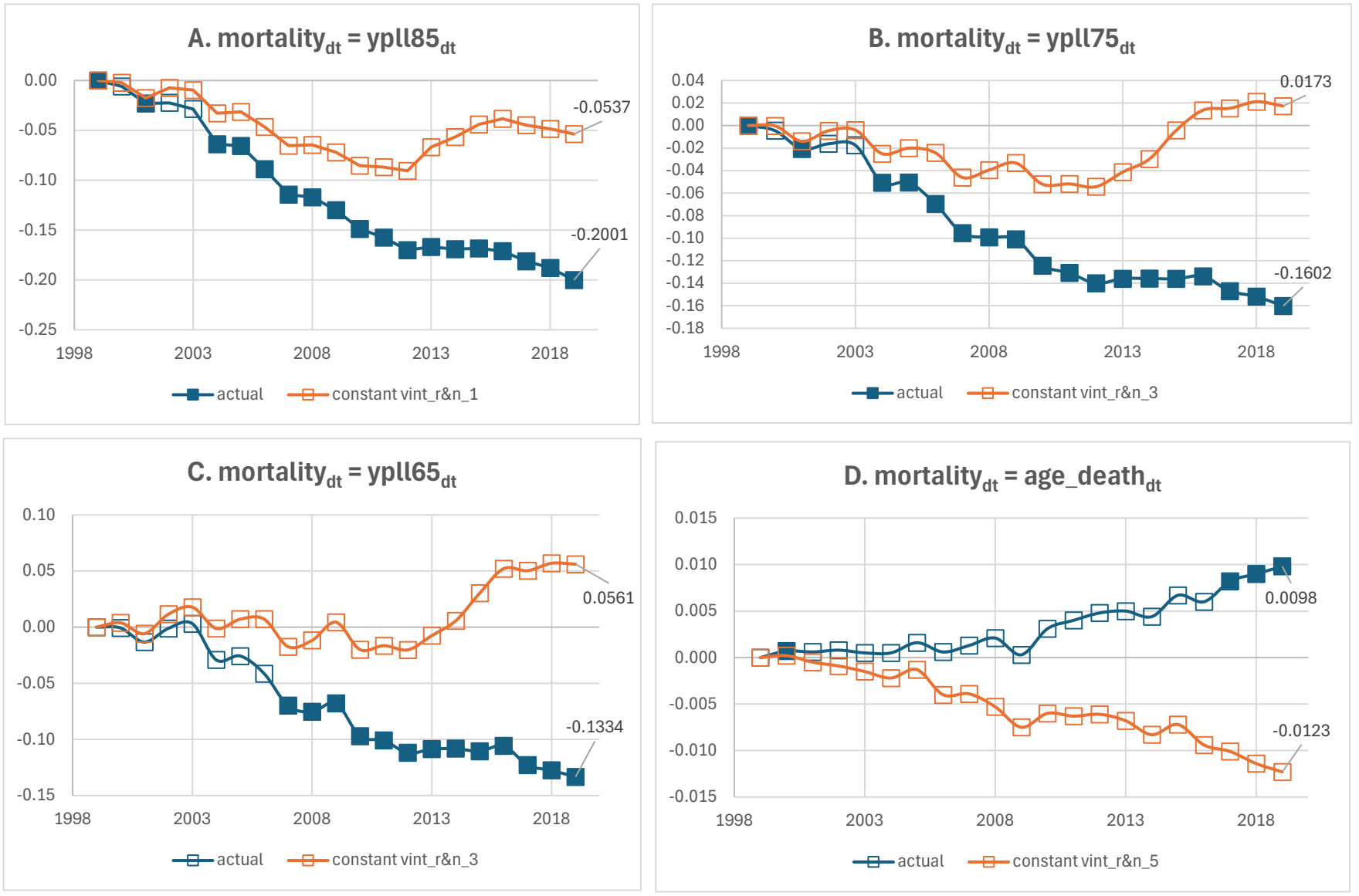




A solid marker indicates a statistically significant (p-value < .05) estimate.
A hollow marker indicates a statistically insignificant estimate.

Figure 5

Actual versus counterfactual (constant lagged vint_r&n) post-1999 change in mortality, 2000-2019



A solid marker indicates that the value in year t is significantly different (p-value < .05) from the 1999 value.

A hollow marker indicates that the value in year t is not significantly different from the 1999 value.

Table 1

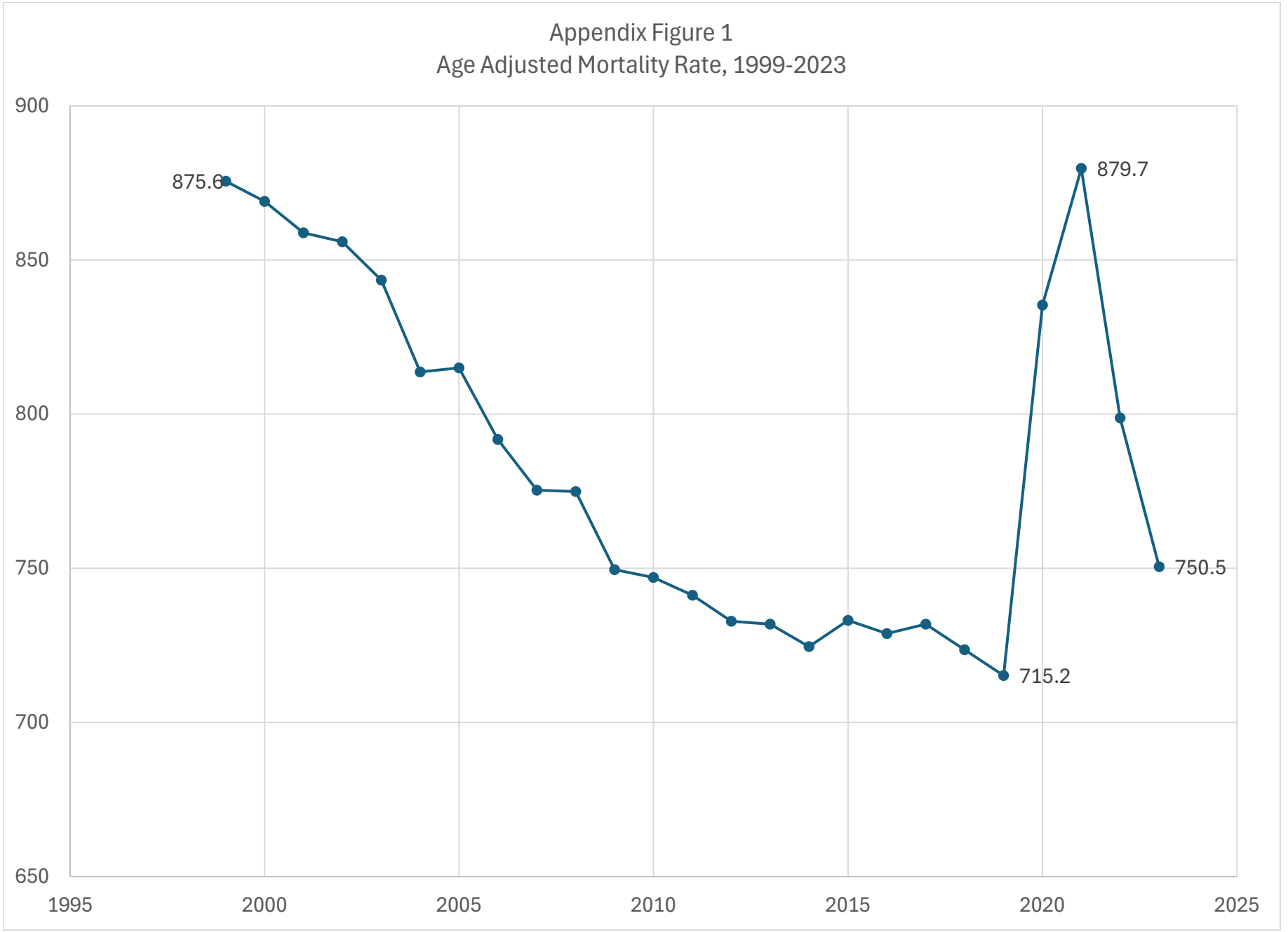
Estimates of β_k from model $\ln(\text{mortality}_{dt}) = \beta_k \text{ vint_r\&n}_{d,t-k} + \alpha_d + \delta_t + \varepsilon_{dt}$

k (lag)	Estimate	Std. Err.	Z	Pr > |Z|		k (lag)	Estimate	Std. Err.	Z	Pr > |Z|
	A. mortality$_{dt}$ = yll85$_{dt}$						**B. mortality$_{dt}$ = yll75$_{dt}$**			
0	**-0.0132**	**0.0058**	**-2.26**	**0.0238**		0	**-0.0152**	**0.0058**	**-2.64**	**0.0083**
1	**-0.0138**	**0.0060**	**-2.30**	**0.0216**		1	**-0.0161**	**0.0059**	**-2.71**	**0.0067**
2	**-0.0139**	**0.0062**	**-2.26**	**0.0241**		2	**-0.0167**	**0.0061**	**-2.73**	**0.0064**
3	**-0.0139**	**0.0063**	**-2.22**	**0.0261**		3	**-0.0172**	**0.0062**	**-2.76**	**0.0058**
4	**-0.0132**	**0.0065**	**-2.05**	**0.0407**		4	**-0.0170**	**0.0064**	**-2.66**	**0.0079**
5	-0.0118	0.0068	-1.73	0.0829		5	**-0.0163**	**0.0067**	**-2.42**	**0.0154**
6	-0.0097	0.0074	-1.32	0.1868		6	**-0.0148**	**0.0073**	**-2.02**	**0.0435**
7	-0.0069	0.0087	-0.80	0.4256		7	-0.0131	0.0086	-1.52	0.1280
8	-0.0070	0.0115	-0.61	0.5443		8	-0.0144	0.0113	-1.28	0.2000
	C. mortality$_{dt}$ = yll65$_{dt}$						**D. mortality$_{dt}$ = age_death$_{dt}$**			
0	**-0.0155**	**0.0053**	**-2.95**	**0.0032**		0	0.0016	0.0008	1.89	0.0583
1	**-0.0166**	**0.0054**	**-3.07**	**0.0021**		1	0.0017	0.0009	1.95	0.0511
2	**-0.0176**	**0.0056**	**-3.13**	**0.0018**		2	**0.0018**	**0.0009**	**2.05**	**0.0400**
3	**-0.0184**	**0.0058**	**-3.16**	**0.0016**		3	**0.0019**	**0.0009**	**2.16**	**0.0306**
4	**-0.0184**	**0.0062**	**-3.00**	**0.0027**		4	**0.0021**	**0.0010**	**2.21**	**0.0272**
5	**-0.0182**	**0.0067**	**-2.71**	**0.0067**		5	**0.0023**	**0.0011**	**2.22**	**0.0263**
6	**-0.0167**	**0.0077**	**-2.18**	**0.0294**		6	**0.0025**	**0.0012**	**2.09**	**0.0363**
7	-0.0151	0.0091	-1.67	0.0955		7	**0.0029**	**0.0014**	**2.04**	**0.0411**
8	-0.0160	0.0121	-1.32	0.1885		8	**0.0038**	**0.0018**	**2.09**	**0.0367**
	E. mortality$_{dt}$ = n_deaths$_{dt}$									
0	-0.0096	0.0088	-1.09	0.2777						
1	-0.0084	0.0087	-0.97	0.3331						
2	-0.0060	0.0087	-0.68	0.4945						
3	-0.0033	0.0094	-0.35	0.7228						
4	0.0011	0.0109	0.10	0.9170						
5	0.0070	0.0132	0.53	0.5953						
6	0.0131	0.0156	0.84	0.4025						
7	0.0229	0.0195	1.17	0.2400						
8	0.0328	0.0259	1.26	0.2060						

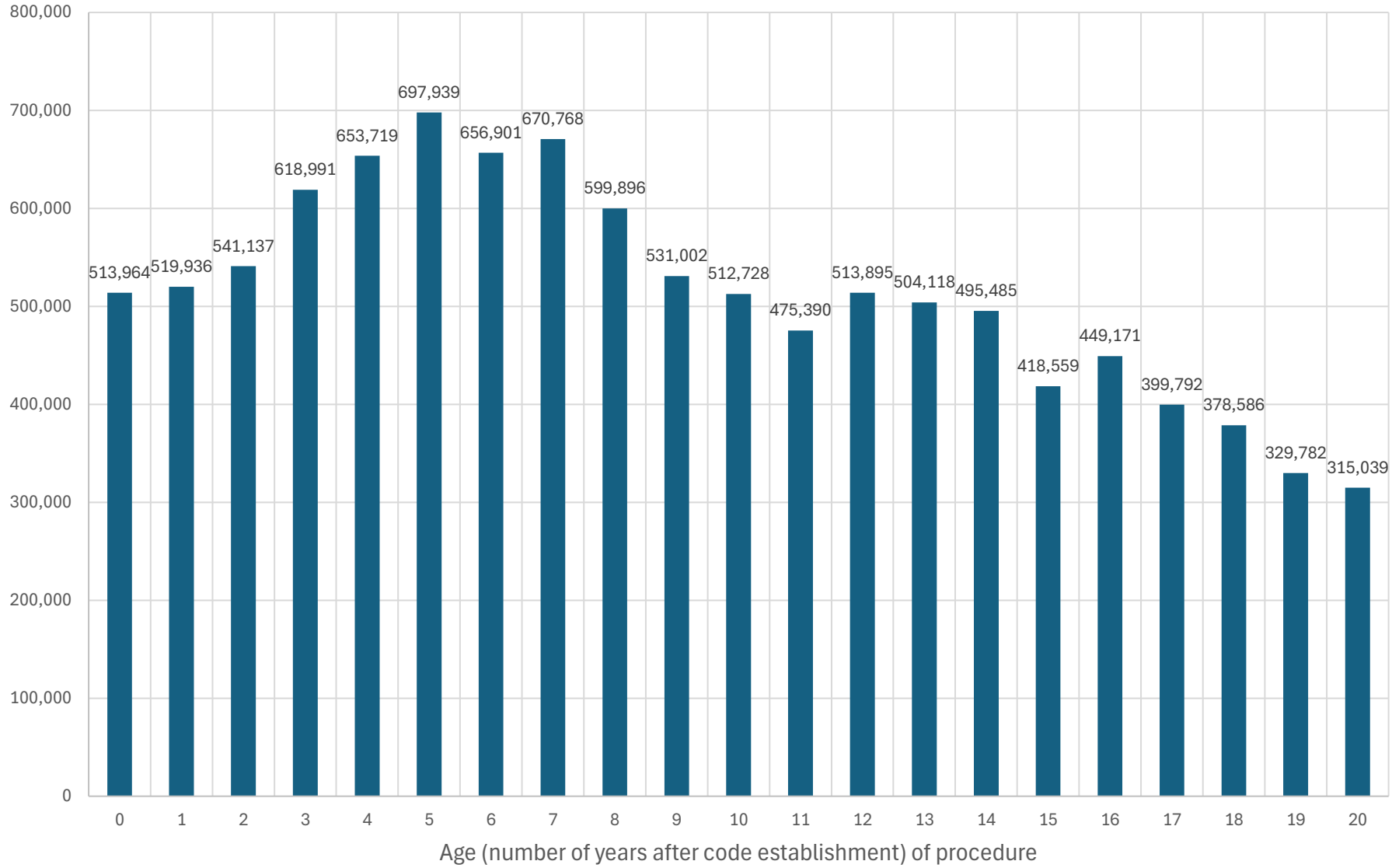
Each estimate is from a separate model.

Estimates in bold are statistically significant (p-value < .05).

Appendix Figure 1
Age Adjusted Mortality Rate, 1999-2023



Appendix Figure 2
Mean number of times each procedure was used,
by age (number of years after code establishment) of procedure



Appendix Table 1

Number of R&N items and procedures by category and subcategory

Anesthesia	**47**
Anesthesia	47
Durable Medical Equipment	**27**
Drugs Administered Through DME	5
Medical/Surgical Supplies	3
Orthotic Devices	3
Other DME	16
Evaluation and Management	**108**
Behavioral Health Services	56
Care Management/Coordination	2
Critical Care Services	2
E&M - Miscellaneous	15
Home Services	15
Observation Care Services	2
Office/Outpatient Services	4
Ophthalmological Services	12
Imaging	**761**
CT Scan	84
Imaging - Miscellaneous	11
Magnetic Resonance	94
Nuclear	136
Standard X-ray	308
Ultrasound	128
Other	**36**
Vision, Hearing, and Speech Services	36

Procedure	**1062**
Breast	42
Cardiovascular	110
Digestive/Gastrointestinal	176
Eye	61
Hematology	1
Musculoskeletal	281
Other Organ Systems	106
Skin	209
Vascular	76
Test	**1324**
Anatomic Pathology	26
Cardiography	66
General Laboratory	131
Molecular Testing	821
Neurologic	102
Pulmonary	37
Pulmonary Function	35
Test - Miscellaneous	106
Treatment	**446**
Chemotherapy	42
Dialysis	11
Injections and Infusions (nononcologic)	249
Physical, Occupational, and Speech Therapy	66
Radiation Oncology	31
Spinal Manipulation	9
Treatment - Miscellaneous	38

Appendix Table 2
HCPCS codes (listed in order of year of HCPCS code establishment) covered in at least one LCD for A02.1 Salmonella sepsis

year_hcpcs	hcpcs	long_description
1982	93005	ELECTROCARDIOGRAM, ROUTINE ECG WITH AT LEAST 12 LEADS; TRACING ONLY, WITHOUT INTERPRETATION AND REPORT
1982	93000	ELECTROCARDIOGRAM, ROUTINE ECG WITH AT LEAST 12 LEADS; WITH INTERPRETATION AND REPORT
1982	93010	ELECTROCARDIOGRAM, ROUTINE ECG WITH AT LEAST 12 LEADS; INTERPRETATION AND REPORT ONLY
1982	93320	DOPPLER ECHOCARDIOGRAPHY, PULSED WAVE AND/OR CONTINUOUS WAVE WITH SPECTRAL DISPLAY (LIST SEPARATELY IN ADDITION TO CODES FOR ECHOCARDIOGRAPHIC IMAGING); COMPLETE
1984	93040	RHYTHM ECG, 1-3 LEADS; WITH INTERPRETATION AND REPORT
1984	93041	RHYTHM ECG, 1-3 LEADS; TRACING ONLY WITHOUT INTERPRETATION AND REPORT
1984	93042	RHYTHM ECG, 1-3 LEADS; INTERPRETATION AND REPORT ONLY
1984	87188	SUSCEPTIBILITY STUDIES, ANTIMICROBIAL AGENT; MACROBROTH DILUTION METHOD, EACH AGENT
1984	87190	SUSCEPTIBILITY STUDIES, ANTIMICROBIAL AGENT; MYCOBACTERIA, PROPORTION METHOD, EACH AGENT
1984	87186	SUSCEPTIBILITY STUDIES, ANTIMICROBIAL AGENT; MICRODILUTION OR AGAR DILUTION (MINIMUM INHIBITORY CONCENTRATION [MIC] OR BREAKPOINT), EACH MULTI-ANTIMICROBIAL, PER PLATE
1984	87181	SUSCEPTIBILITY STUDIES, ANTIMICROBIAL AGENT; AGAR DILUTION METHOD, PER AGENT (EG, ANTIBIOTIC GRADIENT STRIP)
1984	87184	SUSCEPTIBILITY STUDIES, ANTIMICROBIAL AGENT; DISK METHOD, PER PLATE (12 OR FEWER AGENTS)
1988	87187	SUSCEPTIBILITY STUDIES, ANTIMICROBIAL AGENT; MICRODILUTION OR AGAR DILUTION, MINIMUM LETHAL CONCENTRATION (MLC), EACH PLATE (LIST SEPARATELY IN ADDITION TO CODE FOR PRIMARY PROCEDURE)
1989	93312	ECHOCARDIOGRAPHY, TRANSESOPHAGEAL, REAL-TIME WITH IMAGE DOCUMENTATION (2D) (WITH OR WITHOUT M-MODE RECORDING); INCLUDING PROBE PLACEMENT, IMAGE ACQUISITION, INTERPRETATION AND REPORT
1990	93325	DOPPLER ECHOCARDIOGRAPHY COLOR FLOW VELOCITY MAPPING (LIST SEPARATELY IN ADDITION TO CODES FOR ECHOCARDIOGRAPHY)
1990	93321	DOPPLER ECHOCARDIOGRAPHY, PULSED WAVE AND/OR CONTINUOUS WAVE WITH SPECTRAL DISPLAY (LIST SEPARATELY IN ADDITION TO CODES FOR ECHOCARDIOGRAPHIC IMAGING); FOLLOW-UP OR LIMITED STUDY (LIST SEPARATELY IN ADDITION TO CODES FOR
1993	93313	ECHOCARDIOGRAPHY, TRANSESOPHAGEAL, REAL-TIME WITH IMAGE DOCUMENTATION (2D) (WITH OR WITHOUT M-MODE RECORDING); PLACEMENT OF TRANSESOPHAGEAL PROBE ONLY
1993	93314	ECHOCARDIOGRAPHY, TRANSESOPHAGEAL, REAL-TIME WITH IMAGE DOCUMENTATION (2D) (WITH OR WITHOUT M-MODE RECORDING); IMAGE ACQUISITION, INTERPRETATION AND REPORT ONLY
1997	93317	TRANSESOPHAGEAL ECHOCARDIOGRAPHY FOR CONGENITAL CARDIAC ANOMALIES; IMAGE ACQUISITION, INTERPRETATION AND REPORT ONLY

Appendix Table 2
HCPCS codes (listed in order of year of HCPCS code establishment) covered in at least one LCD for A02.1 Salmonella sepsis

year_hcpcs	hcpcs	long_description
1997	93316	TRANSESOPHAGEAL ECHOCARDIOGRAPHY FOR CONGENITAL CARDIAC ANOMALIES; PLACEMENT OF TRANSESOPHAGEAL PROBE ONLY
1997	93315	TRANSESOPHAGEAL ECHOCARDIOGRAPHY FOR CONGENITAL CARDIAC ANOMALIES; INCLUDING PROBE PLACEMENT, IMAGE ACQUISITION, INTERPRETATION AND REPORT
2001	93318	ECHOCARDIOGRAPHY, TRANSESOPHAGEAL (TEE) FOR MONITORING PURPOSES, INCLUDING PROBE PLACEMENT, REAL TIME 2-DIMENSIONAL IMAGE ACQUISITION AND INTERPRETATION LEADING TO ONGOING (CONTINUOUS) ASSESSMENT OF (DYNAMICALLY CHANGING)
2001	87185	SUSCEPTIBILITY STUDIES, ANTIMICROBIAL AGENT; ENZYME DETECTION (EG, BETA LACTAMASE), PER ENZYME
2006	76377	3D RENDERING WITH INTERPRETATION AND REPORTING OF COMPUTED TOMOGRAPHY, MAGNETIC RESONANCE IMAGING, ULTRASOUND, OR OTHER TOMOGRAPHIC MODALITY WITH IMAGE POSTPROCESSING UNDER CONCURRENT SUPERVISION; REQUIRING IMAGE POSTPROC
2006	76376	3D RENDERING WITH INTERPRETATION AND REPORTING OF COMPUTED TOMOGRAPHY, MAGNETIC RESONANCE IMAGING, ULTRASOUND, OR OTHER TOMOGRAPHIC MODALITY WITH IMAGE POSTPROCESSING UNDER CONCURRENT SUPERVISION; NOT REQUIRING IMAGE POST
2008	C8926	TRANSESOPHAGEAL ECHOCARDIOGRAPHY (TEE) WITH CONTRAST, OR WITHOUT CONTRAST FOLLOWED BY WITH CONTRAST, FOR CONGENITAL CARDIAC ANOMALIES; INCLUDING PROBE PLACEMENT, IMAGE ACQUISITION, INTERPRETATION AND REPORT
2008	C8925	TRANSESOPHAGEAL ECHOCARDIOGRAPHY (TEE) WITH CONTRAST, OR WITHOUT CONTRAST FOLLOWED BY WITH CONTRAST, REAL TIME WITH IMAGE DOCUMENTATION (2D) (WITH OR WITHOUT M-MODE RECORDING); INCLUDING PROBE PLACEMENT, IMAGE ACQUISITION
2008	C8927	TRANSESOPHAGEAL ECHOCARDIOGRAPHY (TEE) WITH CONTRAST, OR WITHOUT CONTRAST FOLLOWED BY WITH CONTRAST, FOR MONITORING PURPOSES, INCLUDING PROBE PLACEMENT, REAL TIME 2-DIMENSIONAL IMAGE ACQUISITION AND INTERPRETATION LEADING
2015	87505	INFECTIOUS AGENT DETECTION BY NUCLEIC ACID (DNA OR RNA); GASTROINTESTINAL PATHOGEN (EG, CLOSTRIDIUM DIFFICILE, E. COLI, SALMONELLA, SHIGELLA, NOROVIRUS, GIARDIA), INCLUDES MULTIPLEX REVERSE TRANSCRIPTION, WHEN
2015	93355	ECHOCARDIOGRAPHY, TRANSESOPHAGEAL (TEE) FOR GUIDANCE OF A TRANSCATHETER INTRACARDIAC OR GREAT VESSEL(S) STRUCTURAL INTERVENTION(S) (EG, TAVR, TRANSCATHETER PULMONARY VALVE REPLACEMENT, MITRAL VALVE REPAIR, PARAVALVULAR RE
2022	93319	3D ECHOCARDIOGRAPHIC IMAGING AND POSTPROCESSING DURING TRANSESOPHAGEAL ECHOCARDIOGRAPHY, OR DURING TRANSTHORACIC ECHOCARDIOGRAPHY FOR CONGENITAL CARDIAC ANOMALIES, FOR THE ASSESSMENT OF CARDIAC STRUCTURE(S) (EG, CARDIAC C

Appendix Table 3

1999 and 2019 mortality and R&N treatment data for the top 38 diseases, ranked by number of deaths during 1999-2019

	n_deaths	n_deaths		yll75		age_death		n_r&n		vint_r&n	
358 Cause Recode (ICD-10-CM codes)	**1999-2019**	**1999**	**2019**	**1999**	**2019**	**1999**	**2019**	**1999**	**2019**	**1999**	**2019**
215 All other forms of chronic ischemic heart disease (I20, I25.1-I25.9)	4,423,540	255,317	186,567	823,600	610,454	79.3	79.9	144	291	1990.0	2000.0
93 Of trachea, bronchus and lung (C33-C34)	3,248,862	152,235	139,814	1,088,439	811,992	70.0	72.3	105	229	1986.2	1999.4
211 Acute myocardial infarction (I21-I22)	2,914,111	199,772	104,543	932,348	610,926	76.1	74.6	115	213	1989.8	1998.9
267 Other chronic obstructive pulmonary disease (J44)	2,561,334	99,622	144,869	307,373	511,028	76.9	77.1	136	205	1987.9	1995.0
175 Organic dementia (F01, F03)	1,864,109	28,712	115,125	9,951	50,236	86.8	87.2	82	184	1988.4	1999.9
189 Alzheimer's disease (G30)	1,738,728	44,543	121,539	20,356	53,644	85.1	86.6	113	189	1987.6	1996.8
159 Diabetes mellitus (E10-E14)	1,574,335	68,457	87,795	444,144	645,569	72.7	71.7	234	435	1988.2	1998.2
238 Stroke, not specified as hemorrhage or infarction (I64)	1,495,939	91,121	53,818	163,806	154,125	81.8	80.7				
214 Atherosclerotic cardiovascular disease, so described (I25.0)	1,325,964	72,150	66,459	371,576	501,329	76.2	72.1	1	1	1984.0	1984.0
230 Congestive heart failure (I50.0)	1,182,324	50,833	65,803	79,452	139,744	83.4	83.3	0	1	.	2011.0
257 Pneumonia due to other or unspecified organisms (J16,J18)	1,056,692	57,642	39,123	157,423	165,789	81.9	78.8	86	124	1987.0	1993.7
228 Conduction disorders and cardiac dysrhythmias (I44-I49)	946,871	39,973	56,886	191,077	250,278	77.4	78.4	161	326	1988.6	1999.4
327 Renal failure (N17-N19)	926,348	34,583	50,534	148,826	237,298	77.1	76.6	109	183	1988.9	1997.5
81 Colon (C18)	917,942	48,463	40,710	284,574	298,696	73.4	71.9	92	277	1987.1	2004.1
104 Malignant neoplasm of breast (C50)	877,158	41,557	42,826	432,312	396,333	67.7	69.3	74	291	1986.2	2006.1
125 Other malignant neoplasms of other and unspecified sites (C76-C80, C97)	855,158	43,894	43,506	311,321	274,485	71.5	72.9	326	621	1987.3	1998.1
88 Of pancreas (C25)	764,739	29,113	45,956	194,367	290,714	71.6	71.9	68	266	1986.6	2006.0
23 Septicemia (A40-A41)	751,592	30,434	38,380	170,397	245,501	75.4	73.8	95	150	1987.0	1995.0
207 Hypertensive heart disease (I11)	730,565	22,774	55,581	150,628	386,128	74.9	75.0	98	179	1989.3	1998.3

Appendix Table 3

1999 and 2019 mortality and R&N treatment data for the top 38 diseases, ranked by number of deaths during 1999-2019

	n_deaths	n_deaths		yll75		age_death		n_r&n		vint_r&n	
358 Cause Recode (ICD-10-CM codes)	**1999-2019**	**1999**	**2019**	**1999**	**2019**	**1999**	**2019**	**1999**	**2019**	**1999**	**2019**
194 All other diseases of nervous system (G10-G14, G23-G25, G31, G36-G37, G43-G44, G47-G72, G81-G98)	651,709	17,949	65,572	209,878	346,098	66.2	77.1	365	723	1987.7	1998.4
113 Of prostate (C61)	618,636	31,747	31,673	72,001	90,218	78.5	78.5	66	247	1985.9	2005.5
278 All other diseases of respiratory system (J80-J84,J93-J98)	614,044	22,425	40,745	119,112	185,295	74.8	76.3	175	253	1987.5	1993.9
239 Other cerebrovascular diseases and their sequelae (I67, I69)	612,038	29,530	44,901	51,116	90,581	82.5	83.4	256	491	1988.0	1998.2
236 Intracerebral and other intracranial hemorrhage (I61-I62)	578,363	25,496	28,179	172,279	169,764	72.6	74.5	80	146	1988.5	1997.5
227 Cardiomyopathy (I42)	506,725	27,167	20,389	246,647	185,673	70.3	70.8	123	242	1989.5	1999.3
188 Parkinson's disease (G20-G21)	479,226	14,596	35,327	12,716	35,517	81.4	81.9	152	261	1987.8	1997.3
129 Non-Hodgkin's lymphoma (C82-C85)	438,561	22,831	20,316	172,117	109,555	70.8	74.4	199	337	1987.5	1997.4
273 Pneumonitis due to food and vomit (J69.0)	373,081	15,245	19,192	36,475	67,631	81.7	80.0	1	1	1984.0	1984.0
206 Essential (primary) hypertension (I10)	349,862	9,920	23,089	36,645	105,577	79.3	78.2	61	119	1988.9	1997.3
300 Fibrosis and cirrhosis of liver (K74)	344,866	13,879	20,230	167,741	212,661	64.5	66.3	78	130	1988.0	1996.8
298 Alcoholic liver disease (K70)	344,684	11,971	24,176	241,047	444,014	55.2	56.9	81	133	1987.8	1996.5
85 Liver (C22.0, C22.2-C22.9)	320,165	9,847	20,190	92,753	156,621	68.0	69.6	0	1	.	2019.0
225 Nonrheunatic aortic valve disorders (I35)	310,449	12,218	16,141	25,205	30,206	82.3	84.5	103	186	1989.5	1998.4
118 Of bladder (C67)	302,861	11,916	16,812	47,796	57,232	76.0	77.9	55	130	1985.9	2000.8
109 Of ovary (C56)	300,898	13,641	13,469	116,141	106,071	69.2	70.1	57	235	1986.3	2006.3
293 Vascular disorders and obstruction of intestine without hernia (K55-K56)	299,166	13,747	14,674	49,234	66,530	78.3	77.2	94	181	1987.5	1998.4
122 Of brain (C71)	297,989	12,487	16,909	194,836	211,735	60.8	64.3	73	226	1987.1	2003.2
77 Of esophagus (C15)	294,546	11,923	15,985	100,916	122,814	68.8	69.8	78	157	1986.2	1998.9

Appendix Table 4

Estimates of β_k from model $\ln(\text{mortality}_{dt}) = \beta_k \ln(\text{n_r\&n}_{d,t-k}) + \alpha_d + \delta_t + \varepsilon_{dt}$

k (lag)	Estimate	Std. Err.	Z	Pr > |Z|		k (lag)	Estimate	Std. Err.	Z	Pr > |Z|
	A. $\text{mortality}_{dt} = \text{yll85}_{dt}$						B. $\text{mortality}_{dt} = \text{yll75}_{dt}$			
0	**-0.1769**	**0.0853**	**-2.07**	**0.0380**		0	**-0.1991**	**0.0827**	**-2.41**	**0.0160**
1	**-0.1821**	**0.0889**	**-2.05**	**0.0405**		1	**-0.2096**	**0.0861**	**-2.43**	**0.0149**
2	-0.1803	0.0928	-1.94	0.0521		2	**-0.2156**	**0.0895**	**-2.41**	**0.0160**
3	-0.1784	0.0979	-1.82	0.0684		3	**-0.2184**	**0.0926**	**-2.36**	**0.0183**
4	-0.1691	0.1073	-1.57	0.1153		4	**-0.2147**	**0.0986**	**-2.18**	**0.0295**
5	-0.1465	0.1194	-1.23	0.2200		5	-0.1990	0.1075	-1.85	0.0643
6	-0.1261	0.1318	-0.96	0.3385		6	-0.1800	0.1175	-1.53	0.1256
7	-0.1032	0.1484	-0.70	0.4869		7	-0.1577	0.1314	-1.20	0.2302
8	-0.1449	0.1855	-0.78	0.4348		8	-0.1764	0.1600	-1.10	0.2703
	C. $\text{mortality}_{dt} = \text{yll65}_{dt}$						D. $\text{mortality}_{dt} = \text{age_death}_{dt}$			
0	**-0.1978**	**0.0732**	**-2.70**	**0.0069**		0	0.0202	0.0118	1.71	0.0873
1	**-0.2108**	**0.0771**	**-2.73**	**0.0062**		1	0.0217	0.0123	1.77	0.0770
2	**-0.2214**	**0.0815**	**-2.72**	**0.0066**		2	0.0235	0.0127	1.85	0.0643
3	**-0.2261**	**0.0858**	**-2.64**	**0.0084**		3	0.0250	0.0131	1.91	0.0563
4	**-0.2224**	**0.0937**	**-2.37**	**0.0177**		4	0.0269	0.0141	1.91	0.0561
5	**-0.2088**	**0.1051**	**-1.99**	**0.0470**		5	0.0288	0.0155	1.86	0.0630
6	-0.1858	0.1182	-1.57	0.1160		6	0.0297	0.0171	1.73	0.0829
7	-0.1562	0.1344	-1.16	0.2451		7	0.0317	0.0196	1.62	0.1051
8	-0.1493	0.1616	-0.92	0.3553		8	0.0322	0.0223	1.45	0.1483
	E. $\text{mortality}_{dt} = \text{n_deaths}_{dt}$									
0	-0.1205	0.1273	-0.95	0.3441						
1	-0.0872	0.1374	-0.63	0.5258						
2	-0.0369	0.1576	-0.23	0.8146						
3	0.0077	0.1896	0.04	0.9678						
4	0.0758	0.2354	0.32	0.7474						
5	0.1624	0.2839	0.57	0.5672						
6	0.2239	0.3201	0.70	0.4844						
7	0.3033	0.3632	0.83	0.4038						
8	0.2350	0.4027	0.58	0.5595						

Each estimate is from a separate model.

Estimates in bold are statistically significant (p-value < .05).

Appendix Table 5

MORTALITY BY EDUCATIONAL ATTAINMENT

Estimates of β_k from model $\ln(\text{mortality}_{dt}) = \beta_k \text{ vint_r\&n}_{d,t-k} + \alpha_d + \delta_t + \varepsilon_{dt}$

k (lag)	Estimate	Std. Err.	Z	Pr > |Z|		k (lag)	Estimate	Std. Err.	Z	Pr > |Z|
	0-11 years of education									
	A. mortality$_{dt}$ = yll75$_{dt}$						**D. mortality$_{dt}$ = age_death$_{dt}$**			
0	**-0.0159**	**0.0056**	**-2.83**	**0.0046**		0	0.0012	0.0009	1.36	0.1724
1	**-0.0165**	**0.0058**	**-2.83**	**0.0047**		1	0.0013	0.0009	1.37	0.1698
2	**-0.0171**	**0.0060**	**-2.83**	**0.0046**		2	0.0014	0.0010	1.46	0.1436
3	**-0.0175**	**0.0062**	**-2.83**	**0.0046**		3	0.0016	0.0010	1.61	0.1081
4	**-0.0172**	**0.0063**	**-2.72**	**0.0066**		4	0.0019	0.0011	1.76	0.0782
5	**-0.0168**	**0.0067**	**-2.53**	**0.0113**		5	0.0023	0.0012	1.95	0.0509
6	**-0.0152**	**0.0072**	**-2.11**	**0.0346**		6	0.0026	0.0013	1.95	0.0513
7	-0.0128	0.0082	-1.57	0.1164		7	**0.0030**	**0.0015**	**2.00**	**0.0454**
8	-0.0138	0.0103	-1.34	0.1808		8	**0.0041**	**0.0017**	**2.33**	**0.0198**
	12 years of education									
	B. mortality$_{dt}$ = yll75$_{dt}$						**E. mortality$_{dt}$ = age_death$_{dt}$**			
0	**-0.0229**	**0.0069**	**-3.29**	**0.0010**		0	**0.0016**	**0.0008**	**2.08**	**0.0372**
1	**-0.0238**	**0.0072**	**-3.31**	**0.0009**		1	**0.0017**	**0.0008**	**2.15**	**0.0318**
2	**-0.0243**	**0.0074**	**-3.28**	**0.0010**		2	**0.0018**	**0.0008**	**2.24**	**0.0252**
3	**-0.0245**	**0.0075**	**-3.28**	**0.0010**		3	**0.0019**	**0.0008**	**2.34**	**0.0190**
4	**-0.0240**	**0.0077**	**-3.12**	**0.0018**		4	**0.0020**	**0.0009**	**2.38**	**0.0175**
5	**-0.0229**	**0.0080**	**-2.88**	**0.0040**		5	**0.0022**	**0.0009**	**2.39**	**0.0170**
6	**-0.0208**	**0.0084**	**-2.47**	**0.0134**		6	**0.0024**	**0.0011**	**2.20**	**0.0281**
7	-0.0185	0.0096	-1.93	0.0534		7	**0.0027**	**0.0013**	**2.15**	**0.0318**
8	-0.0189	0.0123	-1.54	0.1241		8	**0.0035**	**0.0016**	**2.22**	**0.0262**
	13+ years of education									
	C. mortality$_{dt}$ = yll75$_{dt}$						**F. mortality$_{dt}$ = age_death$_{dt}$**			
0	**-0.0147**	**0.0056**	**-2.62**	**0.0087**		0	**0.0020**	**0.0007**	**2.85**	**0.0044**
1	**-0.0153**	**0.0058**	**-2.63**	**0.0086**		1	**0.0021**	**0.0007**	**2.94**	**0.0033**
2	**-0.0158**	**0.0061**	**-2.60**	**0.0094**		2	**0.0022**	**0.0007**	**3.05**	**0.0023**
3	**-0.0160**	**0.0062**	**-2.58**	**0.0099**		3	**0.0023**	**0.0007**	**3.17**	**0.0015**
4	**-0.0157**	**0.0065**	**-2.41**	**0.0160**		4	**0.0024**	**0.0008**	**3.15**	**0.0016**
5	**-0.0147**	**0.0070**	**-2.11**	**0.0352**		5	**0.0025**	**0.0008**	**3.02**	**0.0025**
6	-0.0131	0.0077	-1.69	0.0908		6	**0.0026**	**0.0009**	**2.80**	**0.0052**
7	-0.0111	0.0091	-1.22	0.2223		7	**0.0030**	**0.0011**	**2.64**	**0.0082**
8	-0.0115	0.0126	-0.91	0.3612		8	**0.0038**	**0.0016**	**2.39**	**0.0170**

Each estimate is from a separate model.

Estimates in bold are statistically significant (p-value < .05).

Appendix Table 6

MORTALITY OF BLACKS

Estimates of β_k from model $\ln(\text{mortality}_{dt}) = \beta_k \text{ vint_r\&n}_{d,t-k} + \alpha_d + \delta_t + \varepsilon_{dt}$

k (lag)	Estimate	Std. Err.	Z	Pr > |Z|		k (lag)	Estimate	Std. Err.	Z	Pr > |Z|
	A. $\text{mortality}_{dt} = \text{yll85}_{dt}$						**B. $\text{mortality}_{dt} = \text{yll75}_{dt}$**			
0	-0.0048	0.0059	-0.82	0.4134		0	-0.0060	0.0063	-0.95	0.3447
1	-0.0049	0.0059	-0.82	0.4137		1	-0.0061	0.0063	-0.97	0.3330
2	-0.0045	0.0061	-0.73	0.4657		2	-0.0061	0.0065	-0.94	0.3479
3	-0.0040	0.0062	-0.65	0.5173		3	-0.0061	0.0066	-0.92	0.3557
4	-0.0020	0.0062	-0.32	0.7497		4	-0.0045	0.0067	-0.66	0.5078
5	0.0009	0.0063	0.15	0.8826		5	-0.0022	0.0069	-0.32	0.7515
6	0.0046	0.0069	0.67	0.5016		6	0.0011	0.0077	0.14	0.8896
7	0.0088	0.0081	1.09	0.2778		7	0.0042	0.0091	0.46	0.6433
8	0.0112	0.0109	1.03	0.3047		8	0.0049	0.0122	0.40	0.6866
	C. $\text{mortality}_{dt} = \text{yll65}_{dt}$						**D. $\text{mortality}_{dt} = \text{age_death}_{dt}$**			
0	-0.0088	0.0070	-1.27	0.2041		0	0.0017	0.0011	1.54	0.1247
1	-0.0090	0.0068	-1.31	0.1886		1	0.0018	0.0011	1.60	0.1106
2	-0.0091	0.0071	-1.29	0.1959		2	0.0020	0.0012	1.71	0.0867
3	-0.0094	0.0072	-1.30	0.1934		3	0.0022	0.0012	1.86	0.0624
4	-0.0075	0.0074	-1.03	0.3052		4	0.0024	0.0012	1.95	0.0512
5	-0.0052	0.0076	-0.69	0.4878		5	**0.0027**	**0.0013**	**2.04**	**0.0410**
6	-0.0016	0.0086	-0.18	0.8551		6	**0.0029**	**0.0015**	**1.99**	**0.0469**
7	0.0014	0.0104	0.14	0.8919		7	**0.0033**	**0.0016**	**2.02**	**0.0432**
8	0.0023	0.0145	0.16	0.8711		8	**0.0044**	**0.0020**	**2.23**	**0.0260**
	E. $\text{mortality}_{dt} = \text{n_deaths}_{dt}$									
0	-0.0039	0.0088	-0.45	0.6540						
1	-0.0029	0.0087	-0.34	0.7369						
2	-0.0007	0.0086	-0.08	0.9365						
3	0.0018	0.0089	0.20	0.8415						
4	0.0064	0.0097	0.66	0.5075						
5	0.0126	0.0111	1.14	0.2549						
6	0.0193	0.0127	1.52	0.1295						
7	0.0290	0.0155	1.87	0.0622						
8	**0.0404**	**0.0202**	**2.01**	**0.0449**						

Each estimate is from a separate model.

Estimates in bold are statistically significant (p-value < .05).

Geographic variation in the variety and vintage of Medicare services, procedures, and drugs, and its impact on the longevity of elderly Americans

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Geographic variation in the variety and vintage of Medicare services, procedures, and drugs, and its impact on the longevity of elderly Americans

Abstract

There is significant variation across states in the services and procedures provided, and the drugs prescribed, to Medicare beneficiaries. Both the absolute and the relative number and mean vintage of treatments provided to treat different diseases varies across states.

We investigate the effect of four attributes of the services, procedures and drugs provided by Medicare in a state in 2019—the number (or *variety*) and mean vintage of Part B services and procedures, and the variety and mean vintage of Part D drugs—on the longevity (mean age at death) of elderly residents of the state. We estimate models of longevity, by state and medical condition, controlling for state and medical condition fixed effects. This approach controls for all determinants of longevity that are invariant across medical conditions within a state, and for all determinants of longevity that are invariant across states for a given medical condition.

Longevity is significantly positively related to all four measures of the variety and vintage of treatments. The estimates imply that the 2013-2019 increase in the variety and vintage of Part B services and procedures increased longevity by 0.64%, and that the 2013-2019 increase in the variety and vintage of Part D drugs increased longevity by 0.11%. The 2013-2019 increases in the variety and vintage of services, procedures and drugs may have increased longevity by 0.61 years, or 7.35 months. About 1.24 million life-years may have been saved in 2019 by the increase in variety and vintage.

From 2013 to 2019, mean age at death *declined* by 0.28 years. Our estimates suggest that, if the variety and vintage of Medicare treatments had not increased, the decline in longevity would have been larger.

The evidence indicates that the increase in the variety and vintage of services, procedures and drugs increased longevity but did not increase medical costs; indeed, it appears to have reduced Part B expenditure.

I. Introduction

The Centers for Medicare & Medicaid Services (CMS) publishes detailed data on the services and procedures provided to original Medicare (fee-for-service) Part B (medical insurance) beneficiaries by physicians and other healthcare professionals, by service (HCPCS code),[1] state, and year (Centers for Medicare & Medicaid Services (2025a)). CMS also publishes detailed data on the prescription drugs prescribed by individual physicians and other health care providers and paid for under the Medicare Part D Prescription Drug Program, by drug, state, and year (Centers for Medicare & Medicaid Services (2025b)).[2]

Analysis of those data reveals that there is significant variation across states in the services and procedures provided, and the drugs prescribed, to Medicare beneficiaries.[3] One indicator of this is interstate variation in the *number* of distinct HCPCS codes provided.[4] In 2019, the number of distinct HCPCS codes provided in 3 states (California, Florida, and Texas) exceeded 6100, while the number provided in 3 other states (Alaska, Wyoming, and Vermont) was lower than 1900. Not surprisingly, the number of distinct HCPCS codes provided in a state is strongly positively correlated with the number of Medicare beneficiaries in the state.[5] But even in states with similar numbers of HCPCS codes, the specific services and procedures provided may differ. For example, in 2019, the number of HCPCS codes provided in Massachusetts and Maryland were similar: 4724 and 4650, respectively. However, 552 (7.3%) of the HCPCS codes provided in Massachusetts were not provided in Maryland, and 478 (10.3%) of the HCPCS codes provided in Maryland were not provided in Massachusetts.

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[1] The Healthcare Common Procedure Coding System (HCPCS) was established in 1978 by the Federal government to standardize the reporting of medical services, supplies, and equipment, essentially creating a unified system for medical billing across different healthcare providers and payers. While initially voluntary, the Health Insurance Portability and Accountability Act (HIPAA) of 1996 made the use of HCPCS codes mandatory for all healthcare transactions. By the end of 2023, 17,997 HCPCS codes had been established. See Gutmann (2024).

[2] To our knowledge, CMS does not publish detailed data on the services and procedures provided to original Medicare Part A (hospital insurance) beneficiaries by physicians and other healthcare professionals, by service (HCPCS code), state, and year.

[3] Miraldo et al (2019) noted that "innovations do not diffuse uniformly across and within health systems. Due to the high complexity of medical treatment decisions, variations in clinical practice are inherent to healthcare delivery, regardless of technological advances, new ways of working, funding, and burden of disease."

[4] In 2019, 7590 HCPCS codes were provided in at least one state. The mean and median number of states providing each HCPCS code was 26.2 and 26, respectively. In 2019, 1651 drugs (chemical substances) were provided in at least one state. The mean and median number of states providing each drug was 32.4 and 40, respectively.

[5] Some HCPCS codes may be "reasonable and necessary" (as defined in Medicare Coverage Determinations) only for rare diseases, and large states are more likely to have residents with those diseases.

Aside from knowing which states each treatment (service, procedure or drug) was provided in in 2019, we have reliable information about which disease(s) or medical conditions each treatment is used to treat.[6] CMS' Medicare Coverage Determinations (MCD) database (CMS (2025c)) enumerates the medical conditions (coded by ICD-10-CM) for which each HCPCS code is covered by Medicare.[7] Medicare coverage is limited to items and services that are "reasonable and necessary" for the diagnosis or treatment of an illness or injury (and within the scope of a Medicare benefit category). The DrugCentral database (2025) enumerates the FDA-approved indications (uses) of each drug.[8]

By combining the data on the states in which each treatment was provided with the data on the appropriate uses of each treatment, we can calculate the number of treatments that were provided in each state and that were appropriate for each disease in 2019. These calculations reveal that the *relative* number of treatments provided to treat different diseases varied across states. This variation is illustrated by Figure 1, which shows the number of HCPCS codes used to treat 4 medical conditions[9] that were provided in Maryland and Massachusetts in 2019. For two of these conditions (alcoholic liver disease, and cholelithiasis and other disorders of gallbladder), the number of HCPCS codes provided in Massachusetts was larger; for the other two conditions (malignant neoplasm of breast, and leukemia), the number of HCPCS codes provided in Maryland was larger.

A third type of information available about each treatment is its *vintage*: the first year in which it became available. We will define the vintage of a HCPCS code as the year in which the code was established by CMS, and the vintage of a drug as the year in which the drug was

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[6] CMS publishes data on the quantity of each service, procedure, and drug provided in each state, but not on the quantity of each service, procedure, and drug provided for each disease in each state.

[7] This database contains 2.4 million links between HCPCS codes and covered disease (ICD-10-CM) codes. There are two types of MCDs: National Coverage Determinations (NCDs) and Local Coverage Determinations (LCDs). NCDs are binding determinations that are made for the entire country and apply to all Medicare beneficiaries. When there is no national coverage policy, Medicare contractors can establish LCDs: they can decide to cover an item or service at the local level. Unfortunately, CMS' Medicare Coverage Determinations (MCD) database only contains data on LCDs; it is not possible to construct similar data from NCDs. However, Moneer et al (2014) noted that "local coverage determinations…represent the vast majority of Medicare's coverage decisions for new technologies." According to the Medicare Coverage Database (CMS (2025c)), as of 21 December 2024, there were 338 NCDs and 2324 LCDs. HCPCS listed in LCDs accounted for 67% of services provided and 73% of Medicare Part B expenditure in 2022.

[8] The DrugCentral omop_relationship file enumerates 11,775 indications (coded by snomed_conceptid) of 2681 drugs. The SNOMED CT to ICD-10-CM Map (National Library of Medicine (2025)) can be used to map snomed_conceptids to ICD-10-CM codes.

[9] Medical conditions are classified by 113 ICD-10 Cause of Death Recode.

approved by the FDA. Calculations reveal that the relative mean vintage of treatments provided to treat different diseases also varied across states.

In this study, we will investigate the effect of four attributes of the services, procedures and drugs provided by Medicare in a state in 2019—the number (or *variety*) and mean vintage of Part B services and procedures, and the variety and mean vintage of Part D drugs[10]—on the longevity of elderly residents of the state.

Longevity increase is a very important part of economic growth, broadly defined. Nordhaus (2003) argued that "improvements in health status have been a major contributor to economic welfare over the twentieth century. To a first approximation, the economic value of increases in longevity in the last hundred years is about as large as the value of measured growth in non-health goods and services."

Numerous authors have provided both theoretical and empirical support for the hypothesis that increased product variety is an important source of economic growth. Dixit and Stiglitz (1977, p. 297) argued that "less variety…entails some welfare loss." Judd (1985) and Romer (1990) modeled growth based on horizontal product innovations, using the Dixit-Stiglitz (1977) model of product variety. Segerstrom et al (1990) noted that most of the product-life-cycle literature has treated product innovation as being the introduction of greater variety. Grossman and Helpman (1991, p. 53) treat "technology-based growth as a process of generating an ever-expanding *variety* of horizontally differentiated products" [emphasis added]. Their consumption index exhibits *love of variety* over an infinite set of horizontally differentiated products, as in Dixit and Stiglitz. Utilizing panel data for 19 OECD countries, Funke and Ruhwedel (2001) found that an index of relative product variety was significantly positively correlated across countries with relative per capita income levels.

There is also theoretical and empirical support for the hypothesis that the *vintage* of technology or capital has a positive effect on economic growth. As noted by Jovanovic and Yatsenko (2012), in "the Spence–Dixit–Stiglitz tradition…new goods [are] of higher quality than old goods." In 1987, when the Royal Swedish Academy of Sciences (1987) awarded the Nobel Prize in Economic Sciences to Robert Solow for his contributions to the theory of economic

[10] Some Part B services and procedures involve drugs—chemotherapy and injections and infusions (nononcologic) accounted for about 18% of Part B expenditure in 2019—so there may be some overlap between the Part B and Part D measures.

growth, it noted that "the most important aspect of Solow's article was not so much the empirical outcome, but the method of analyzing 'vintage capital'."

We will conduct 2-way fixed effects analyses: we will estimate models of longevity, by state and medical condition, controlling for state and medical condition fixed effects. This approach controls for all determinants of longevity that are invariant across medical conditions within a state (e.g., state mean income, education, and quality of medical care), and for all determinants of longevity that are invariant across states for a given medical condition.

Although life expectancy, calculated from age-specific death rates using life table methods, is undoubtedly the best-known measure of longevity, life expectancy cannot be calculated for specific diseases (causes of death). However, an alternative measure of longevity—mean age at time of death—can be calculated for specific diseases. As shown in Figure 2, mean age at time of death and life expectancy are strongly positively correlated across states. We will analyze the variation in mean age at time of death in 2019, by state (N = 51) and medical condition (N = 53).

Two previous studies employed an approach similar to the approach we will use. Using data on 31 diseases in 11 European countries, Lichtenberg (2019) found that the larger the relative number of drugs for a disease that were launched during 1982-2015 in a country, the lower the relative disability in 2015 of patients with that disease in that country, controlling for the average level of disability in that country and from that disease, and the number of patients with the disease and their mean age. Lichtenberg (2022) analyzed relative longevity (mean age at time of death) associated with different diseases in 26 high-income countries during 2006–2016. Both of those studies analyzed the effect of only one measure of medical care provision—the number or mean vintage of drugs sold.[11] As noted above, we will analyze the effect of four measures of medical care provision. According to Cubanski and Neuman (2023), in 2021, spending on physician services and other Medicare part B services was almost four times as large as Medicare Part D spending.

In the next section, we present our econometric model of longevity. Data sources and descriptive statistics are presented in section III. Empirical results are presented in section IV. Implications of the estimates are discussed in section V. The final section provides a summary.

[11] That study found that the higher the vintage of drugs available to treat a disease in a country, the higher mean age at death from the disease was, controlling for fixed disease and country effects.

II. Econometric model of longevity

To assess the effect of four attributes of the services, procedures and drugs provided by Medicare in a state in 2019 on the longevity of elderly residents of the state, we will estimate several variants of the following model:

$$\ln(age_death_{cs}) = \beta_1 \ln(n_hcpcs_{cs}) + \beta_2 vint_hcpcs_{cs} + \beta_3 \ln(n_drug_{cs}) + \beta_4 vint_drug_{cs} + \gamma \ln(n_deaths_{cs}) + \alpha_c + \delta_s + \varepsilon_{cs} \quad (1)$$

where

age_death_{cs} = mean age (in years) at time of death of decedents age 65 and over who died from medical condition (underlying cause) c in state s

n_hcpcs_{cs} = the number of HCPCS codes used to treat medical condition c that were provided to original Medicare (fee-for-service) Part B (medical insurance) beneficiaries in state s

$vint_hcpcs_{cs}$ = the mean vintage of HCPCS codes used to treat medical condition c that were provided to original Medicare Part B beneficiaries in state s

n_drug_{cs} = the number of drugs used to treat medical condition c that were prescribed by individual physicians and other health care providers and paid for under the Medicare Part D Prescription Drug Program in state s

$vint_drug_{cs}$ = the mean vintage of drugs used to treat medical condition c that were prescribed by individual physicians and other health care providers and paid for under the Medicare Part D Prescription Drug Program in state s

n_deaths_{cs} = the number of decedents age 65 and over who died from medical condition (underlying cause) c in state s

α_c = a fixed effect for medical condition c

δ_s = a fixed effect for state s

n_hcpcs_{cs} is defined as follows:

$$n_hcpcs_{cs} = \sum_h hcpcs_state_{hs}\ hcpcs_treat_{hc}$$

where

$hcpcs_state_{hs}$ = 1 if HCPCS code h was provided in state s
= 0 if HCPCS code h was not provided in state s

$hcpcs_treat_{hc}$ = 1 if HCPCS code h is used to treat medical condition c
= 0 if HCPCS code h is not used to treat medical condition c

$vint_hcpcs_{cs}$ is defined as follows:

$$vint_hcpcs_{cs} = (\sum_h hcpcs_year_h \; hcpcs_state_{cs} \; hcpcs_treat_{hc}) / n_hcpcs_{cs}$$

where $hcpcs_year_h$ = the year of establishment of HCPCS code h.

n_drug_{cs} is defined as follows:

$$n_drug_{cs} = \sum_i ingred_state_{is} \; ingred_treat_{ic}$$

where

$ingred_state_{is}$ = 1 if chemical ingredient i was provided in state s
= 0 if chemical ingredient i was not provided in state s

$ingred_treat_{ic}$ = 1 if chemical ingredient i is used to treat (indicated for) medical condition c
= 0 if chemical ingredient i is not used to treat (indicated for) medical condition c

$vint_drug_{cs}$ is defined as follows:

$$vint_drug_{cs} = (\sum_i FDA_year_i \; ingred_state_{is} \; ingred_treat_{ic}) / n_drug_{cs}$$

where FDA_year_i = the FDA approval year of chemical ingredient i

Eq. (1) will be estimated by weighted least squares, weighting by n_deaths_{cs}. Disturbances will be clustered within states. Medical conditions are classified by 113 ICD-10 Cause of Death Recode (Research Data Assistance Center (2025)). External causes of death are excluded.

III. Data sources and descriptive statistics

Mortality data. Data on mean age at time of death and the number of deaths in 2019, by 113 ICD-10 underlying cause and state, were constructed from data downloaded from the *Mortality 1999-2020 on CDC WONDER Online Database* (Centers for Disease Control and Prevention (2021)). That database provides data on the number of deaths, by underlying cause, state, and single year of age at time of death.[12] Data on life expectancy at age 65 in 2019, by state, were obtained from the *United States Mortality DataBase* (University of California Department of Demography (2025)).

[12] When the number of deaths is less than 10, the data are suppressed.

Medicare Part B data. Data on hcpcs_state$_{hs}$ (an indicator of whether HCPCS code h was provided in state s in 2019) was constructed from the *Medicare Physician & Other Practitioners - by Geography and Service database* (CMS (2025a)). Data on hcpcs_treat$_{hc}$ (an indicator of whether HCPCS code h is used to treat medical condition c) were constructed from the *article_x_hcpc_code* and *article_x_icd10_covered* tables of the *Current and Retired Articles* section (Centers for Medicare and Medicaid Services (2025d)) of the *Medicare Coverage Determinations (MCD) database* (Centers for Medicare and Medicaid Services (2025c)). The ICD-10-CM codes in the MCD database are quite detailed; we used the 2019 *Multiple Cause-of-Death Mortality Data* (National Bureau of Economic Research (2025)) to map ICD-10-CM codes to 113 ICD-10 Cause of Death Recodes. Data on hcpcs_year$_{h}$ (the year of establishment of HCPCS code h) were obtained from the *Restructured BETOS Classification System* (Centers for Medicare and Medicaid Services (2025e)). Data on Medicare Part B and Part A program payments per traditional Medicare enrollee were obtained from KFF (2025).

Medicare Part D data. Data on ingred_state$_{is}$ (an indicator of whether chemical ingredient i was provided in state s in 2019) was constructed from the *Medicare Part D Prescribers - by Geography and Drug database* (CMS (2025a)). Data on ingred_treat$_{ic}$ (an indicator of whether chemical ingredient i is used to treat (indicated for) medical condition c) were constructed from the *Omop_relationship* and *Synonyms* tables of the DrugCentral (2025) database, and the *SNOMED CT to ICD-10-CM Map* (National Library of Medicine (2025)). Data on FDA_year$_{i}$ (the FDA approval year of chemical ingredient i) were obtained from the *Approval* table of the DrugCentral (2025) database.

Descriptive statistics. Data on the number of deaths and weighted sample means in 2013 and 2019 are shown in Table 1. Between 2013 and 2019, mean age at death declined by 0.3%, from 81.7 to 81.4 years. The mean number of HCPCS codes and drugs provided to treat a medical condition increased by 12.2% and 14.5%, respectively. The mean vintage of HCPCS codes and drugs provided to treat a medical condition increased by 2.71 and 4.48 years, respectively.

Data on the number of deaths and weighted sample means, by medical condition in 2019, are shown in Table 2. Our sample includes 53 medical conditions, which accounted for 70% of the 2.04 million deaths from nonexternal causes of elderly (age 65 and over) decedents in 2019. To be included in our sample, both n_hcpcs$_{cs}$ and n_drug$_{cs}$ had to be positive numbers. Data on

the number of deaths and weighted sample means, by state in 2019, are shown in Appendix Table 1.

IV. Empirical results

Estimates of parameters of several variants of eq. (1), all based on 1425 observations, are presented in Table 3. The first four models each contain just one of the four measures of the variety and vintage of services, procedures and drugs. The last three models contain multiple measures.[13]

In model 1, the only regressor (aside from medical condition and state fixed effects) is the log of n_hcpcs_{cs} (the number of HCPCS codes used to treat medical condition c that were provided to original Medicare Part B beneficiaries in state s). The estimate of β_1 is positive and highly significant (p-value = 0.0010). This indicates that the greater the number (or variety) of services and procedures that are used to treat medical condition c that were provided to original Medicare Part B beneficiaries in state s, the higher the mean age at time of death of decedents from cause c in state s, controlling for medical condition and state fixed effects. As shown in column 6, from 2013 to 2019, the weighted mean value of $\ln(n_hcpcs_{cs})$ increased by 0.115, so the estimate of β_1 implies that the 2013-2019 increase in n_hcpcs_{cs} increased $\ln(age_death_{cs})$ by 0.0029 (= 0.0254 * 0.115).

In model 2, the only regressor is $vint_hcpcs_{cs}$ (the mean vintage of HCPCS codes used to treat medical condition c that were provided to original Medicare Part B beneficiaries in state s). The estimate of β_2 is also positive and highly significant (p-value < 0.0001). It implies that the 2013-2019 increase in $vint_hcpcs_{cs}$ increased $\ln(age_death_{cs})$ by 0.0072 (= 0.0027 * 2.7).

In model 3, the only regressor is the log of n_drug_{cs} (the number of drugs used to treat medical condition c that were prescribed by individual physicians and other health care providers and paid for under the Medicare Part D Prescription Drug Program in state s). The estimate of β_3 is also positive and highly significant (p-value < 0.0001). In model 4, the only regressor is $vint_drug_{cs}$ (the mean vintage of drugs used to treat medical condition c that were prescribed by individual physicians and other health care providers and paid for under the Medicare Part D

[13] Estimates of γ (the coefficient of $\ln(n_deaths_{cs})$) were positive but at most only marginally significant in all versions of the model, and inclusion of $\ln(n_deaths_{cs})$ had little effect on estimates of the other parameters, so this variable is excluded from the models whose estimates are shown in Table 3.

Prescription Drug Program in state s). The estimate of β_4 is also positive and highly significant (p-value < 0.0001).

Longevity is significantly positively related to all four measures of the variety and vintage of treatments. The four measures are highly positively correlated with one another. For example, the estimate of π from the regression $\ln(n_hcpcs_{cs}) = \pi\ vint_hcpcs_{cs} + \alpha_c + \delta_s + \varepsilon_{cs}$ is 0.0582 (Z = 18.92; p-value < .0001). Model 5 is a version of eq. (1) that includes both $\ln(n_hcpcs_{cs})$ and $vint_hcpcs_{cs}$ as regressors. The estimate of β_1 is negative and significant, and the estimate of β_2 is positive and significant. The net effect of the mean 2013-2019 change in Part B services and procedures on longevity is the weighted sum of these estimates ((0.115 * β_1) + (2.700 * β_2) = .0082), where the weights are the 2013-2019 weighted mean changes in $\ln(n_hcpcs_{cs})$ and $vint_hcpcs_{cs}$.

Model 6 is a version of eq. (1) that includes both $\ln(n_drug_{cs})$ and $vint_drug_{cs}$ as regressors. The estimate of β_3 is positive and significant, and the estimate of β_4 is insignificant. The net effect of the mean 2013-2019 change in Part D drugs on longevity is the weighted sum of these estimates ((0.134 * β_3) + (4.500 * β_4) = .0015), where the weights are the 2013-2019 weighted mean changes in $\ln(n_drug_{cs})$ and $vint_drug_{cs}$.

Model 7 is a version of eq. (1) that includes all four measures of the variety and vintage of services, procedures and drugs. The estimates of β_1 and β_2 imply that the 2013-2019 increase in the variety and vintage of Part B services and procedures increased longevity by 0.64%, and the estimates of β_3 and β_4 imply that the 2013-2019 increase in the variety and vintage of Part D drugs increased longevity by 0.11%. The estimated total increase in longevity is 0.75%.

V. Discussion

As shown in Table 2, mean age at death in 2019 was 81.4 years, so our most general model (model 7) implies that the 2013-2019 increases in the variety and vintage of services, procedures and drugs may have increased longevity by 0.61 years (= 0.75% * 81.4 years), or 7.35 months. There were 2.04 million deaths from nonexternal causes of elderly (age 65 and over) decedents in 2019, so about 1.24 million (= 0.61 * 2.04 million) life-years may have been saved in 2019 by the increase in variety and vintage.

As shown in Table 1, from 2013 to 2019, mean age at death *declined* by 0.28 years (3.38 months). Our estimates suggest that, if the variety and vintage of Medicare treatments had not increased, the decline in longevity would have been larger: 0.89 (= 0.28 + 0.61) years. Increasing obesity and chronic disease prevalence are potential causes of declining longevity. From 1999-2000 through 2017-March 2020, US obesity prevalence increased from 30.5% to 41.9%, and the prevalence of severe obesity increased from 4.7% to 9.2%. Obesity-related conditions include heart disease, stroke, type 2 diabetes and certain types of cancer. These are among the leading causes of preventable, premature death (Centers for Disease Control and Prevention (2024)). And between 2007 and 2018, the prevalence of 14 out of 21 chronic conditions among male Medicare beneficiaries increased, and the prevalence of 16 out of 21 chronic conditions among female beneficiaries increased (Centers for Medicare and Medicaid Services (2025f)).

The increase in the variety and vintage of services, procedures and drugs may have increased longevity, but it may also have increased medical costs; it might not have been cost-effective. Unfortunately, data on Medicare expenditure, by medical condition and state, are not available. However, data on Medicare Part B and Part A (hospital insurance) program payments per traditional Medicare enrollee, by state and year (2013-2021), are available from KFF (2025). To explore the effect of the variety and vintage of services, procedures and drugs on average Part B and Part A expenditure, we estimated variants of the following model:

$$\ln(avg_cost_{st}) = \rho_1 \ln(n_hcpcs_{st}) + \rho_2 vint_hcpcs_{st} + \rho_3 \ln(n_drug_{st}) + \rho_4 vint_drug_{st} + \delta_s + \alpha_t + \varepsilon_{st} \quad (2)$$

where

avg_cost_{st} = Medicare Part B or Part A program payments per traditional Medicare enrollee in state s in year t (t = 2013, 2019)

n_hcpcs_{st} = the number of HCPCS codes that were provided to original Medicare (fee-for-service) Part B (medical insurance) beneficiaries in state s in year t

$vint_hcpcs_{st}$ = the mean vintage of HCPCS codes that were provided to original Medicare Part B beneficiaries in state s in year t

n_drug_{st} = the number of drugs that were prescribed by individual physicians and other health care providers and paid for under the Medicare Part D Prescription Drug Program in state s in year t

$vint_drug_{st}$ = the mean vintage of drugs that were prescribed by individual physicians and other health care providers and paid for under the Medicare Part D Prescription Drug Program in state s in year t

δ_s = a fixed effect for state s

α_t = a fixed effect for year t

Eq. (2) was estimated by weighted least squares, weighting by the number of traditional Medicare Part B or Part A enrollees in state s in year t. Disturbances were clustered within states.

Estimates of parameters of several variants of eq. (2), all based on 102 observations, are presented in Table 4. In models 8-12, the dependent variable is the log of Medicare Part B program payments per traditional Medicare part B enrollee in state s in year t. Models 8-11 include single measures of treatment variety or vintage. Average Part B expenditure is significantly inversely related to $\ln(n_drug_{st})$ and marginally significantly (p-value < .09) inversely related to $\ln(n_hcpcs_{st})$ and $vint_hcpcs_{st}$. Model 12 includes all 4 measures of treatment variety or vintage. The joint effect of the 2013-2019 increases in treatment variety and vintage is negative and significant (p-value = .0174). The estimates of this model imply that the 2013-2019 increases in treatment variety and vintage *reduced* average Part B expenditure by 14.5%.

In models 13-17, the dependent variable is the log of Medicare Part A program payments per traditional Medicare part A enrollee in state s in year t. Models 13-16 include single measures of treatment variety or vintage. Average Part A expenditure is significantly inversely related to $\ln(n_drug_{st})$, $\ln(n_hcpcs_{st})$ and $vint_drug_{st}$. Model 17 includes all 4 measures of treatment variety or vintage. The joint effect of the 2013-2019 increases in treatment variety and vintage is far from significant. The estimates of this model imply that the 2013-2019 increases in treatment variety and vintage had no effect on average Part A expenditure.

Overall, the evidence indicates that the increase in the variety and vintage of services, procedures and drugs increased longevity but did not increase medical costs; indeed, it appears to have reduced Part B expenditure.

VI. Summary and conclusions

There is significant variation across states in the services and procedures provided, and the drugs prescribed, to Medicare beneficiaries. Both the absolute and the relative number and mean vintage of treatments provided to treat different diseases varies across states.

We investigated the effect of four attributes of the services, procedures and drugs provided by Medicare in a state in 2019—the number (or *variety*) and mean vintage of Part B services and procedures, and the variety and mean vintage of Part D drugs—on the longevity (mean age at death) of elderly residents of the state. We estimated models of longevity, by state and medical condition, controlling for state and medical condition fixed effects. This approach controls for all determinants of longevity that are invariant across medical conditions within a state, and for all determinants of longevity that are invariant across states for a given medical condition.

Longevity is significantly positively related to all four measures of the variety and vintage of treatments. The estimates implied that the 2013-2019 increase in the variety and vintage of Part B services and procedures increased longevity by 0.64%, and that the 2013-2019 increase in the variety and vintage of Part D drugs increased longevity by 0.11%. The 2013-2019 increases in the variety and vintage of services, procedures and drugs may have increased longevity by 0.61 years, or 7.35 months. About 1.24 million life-years may have been saved in 2019 by the increase in variety and vintage.

From 2013 to 2019, mean age at death declined by 0.28 years. Our estimates suggest that, if the variety and vintage of Medicare treatments had not increased, the decline in longevity would have been larger.

The evidence indicates that the increase in the variety and vintage of services, procedures and drugs increased longevity but did not increase medical costs; indeed, it appears to have reduced Part B expenditure.

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Figure 1
Number of HCPCS codes used to treat 4 medical conditions provided in Maryland and Massachusetts in 2019

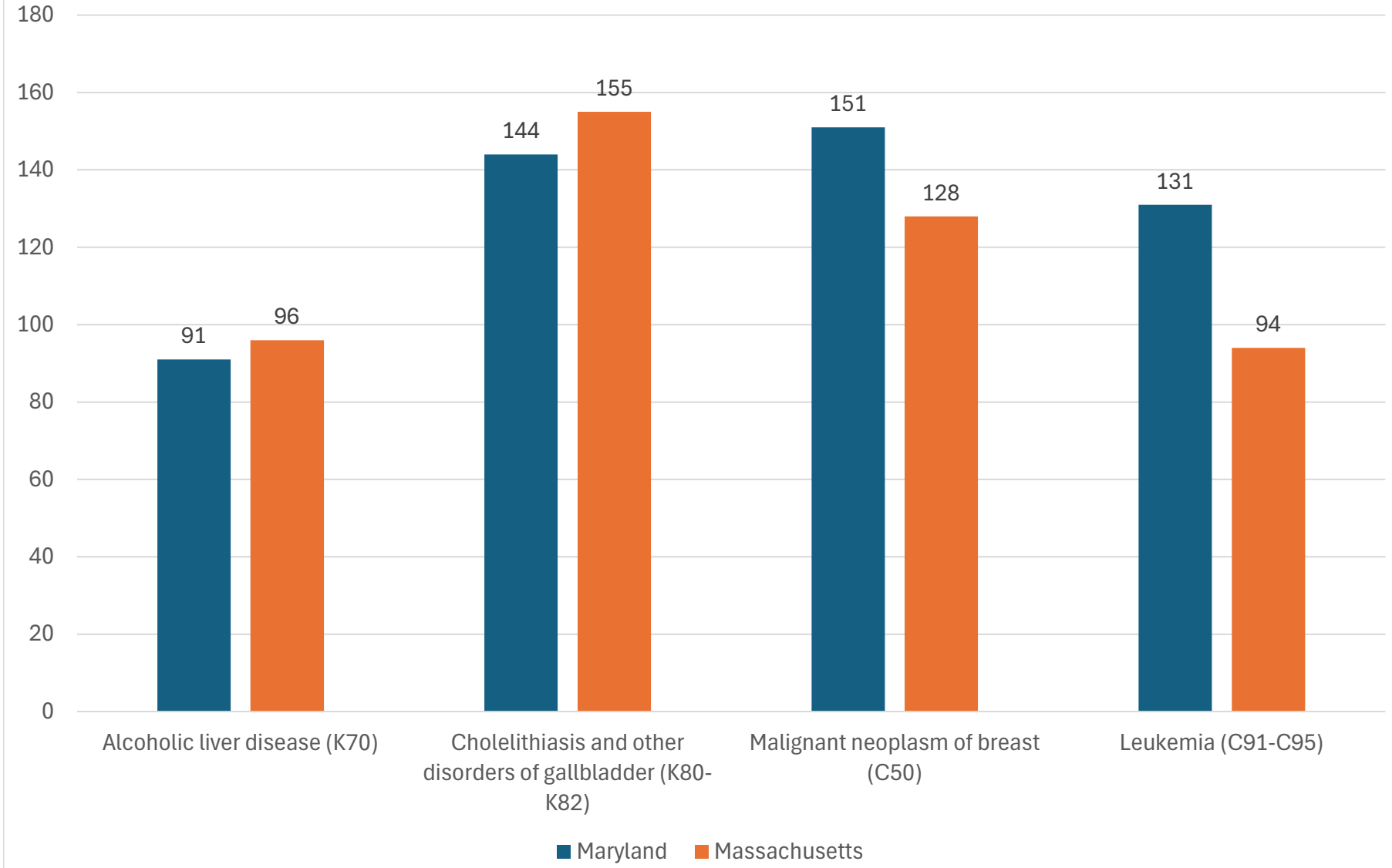
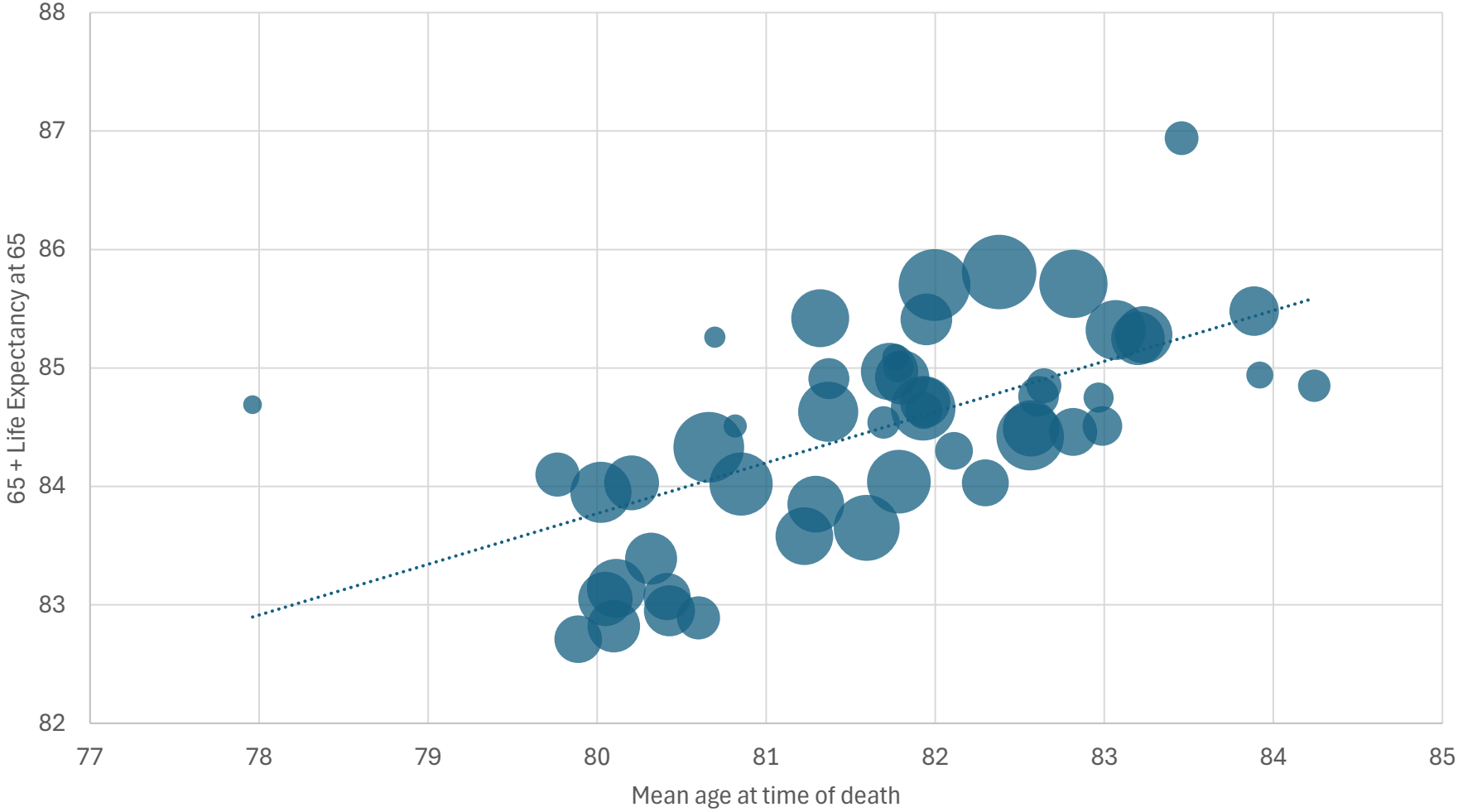


Figure 2
Correlation across states between
mean age at time of death of elderly (age 65 and over) decedents and
(65 + life expectancy at 65), 2019



Bubble area is proportional to number of deaths in 2019.

Table 1

Number of deaths and weighted sample means in 2013 and 2019

		weighted (by n_deaths) means				
year	**n_deaths**	**age_death**	**n_hcpcs**	**vint_hcpcs**	**n_drug**	**vint_drug**
2013	1,296,948	81.67	192.1	1994.7	18.1	1987.2
2019	1,432,798	81.39	215.6	1997.4	20.7	1991.7
% change		0.00	12.2%		14.5%	
change				2.71		4.48

Table 2

No. of deaths and weighted sample means, by medical condition, 2019

Medical condition	n_deaths	age_death	n_hcpcs	vint_hcpcs	n_drug	vint_drug
53 medical conditions	**1,432,798**	**81.4**	**215.6**	**1997.4**	**20.7**	**1991.7**
Certain other intestinal infections (A04,A07-A09)	1,941	81.7	47.6	1997.2	12.4	1988.9
Septicemia (A40-A41)	25,760	79.9	107.1	1993.1	19.1	1974.2
Viral hepatitis (B15-B19)	384	68.3	11.1	1995.7	7.5	1998.2
Human immunodeficiency virus (HIV) disease (B20-B24)	190	67.1	158.1	1999.0	54.0	1992.8
Other and unspecified infectious and parasitic diseases and their sequelae (A00,A05,A20-A36,A42-A44,A48-A49,A54-A79,A81-A82,A85.0-A85.1,A85.8,A86-B04,B06-B09,B25-B49,B55-B99)	2,027	78.3	578.6	1995.6	116.6	1982.4
Malignant neoplasms of lip, oral cavity and pharynx (C00-C14)	2,531	74.7	217.2	1996.5	1.3	1999.4
Malignant neoplasm of esophagus (C15)	5,065	74.6	126.2	1997.0	1.8	2013.9
Malignant neoplasm of stomach (C16)	3,587	76.9	142.3	1998.7	3.9	1987.7
Malignant neoplasms of colon, rectum and anus (C18-C21)	32,774	78.3	176.3	2000.6	5.2	1989.2
Malignant neoplasms of liver and intrahepatic bile ducts (C22)	15,336	74.4	146.0	1998.3	4.3	2009.7
Malignant neoplasm of pancreas (C25)	30,632	76.5	152.7	2001.6	3.1	1984.5
Malignant neoplasm of larynx (C32)	69	73.8	175.1	1997.5	1.0	2004.0
Malignant neoplasms of trachea, bronchus and lung (C33-C34)	103,812	76.6	168.0	1997.4	12.8	2002.6
Malignant melanoma of skin (C43)	1,836	77.2	221.8	1993.0	10.1	2005.2
Malignant neoplasm of breast (C50)	23,153	77.6	156.2	2000.6	22.7	1993.6
Malignant neoplasm of cervix uteri (C53)	99	67.8	105.3	1998.6	1.1	2003.6
Malignant neoplasms of corpus uteri and uterus, part unspecified (C54-C55)	4,560	74.0	104.2	1998.5	3.8	1987.9
Malignant neoplasm of ovary (C56)	5,214	75.4	143.3	2001.7	8.0	1996.4
Malignant neoplasm of prostate (C61)	24,792	80.4	147.0	2000.1	4.5	2012.9
Malignant neoplasms of kidney and renal pelvis (C64-C65)	5,847	76.1	113.0	1999.0	11.4	2006.4
Malignant neoplasms of meninges, brain and other parts of central nervous system (C70-C72)	4,025	73.9	220.3	2000.7	1.1	2002.9
Non-Hodgkin's lymphoma (C82-C85)	12,302	78.9	203.0	1997.0	34.6	1978.0
Leukemia (C91-C95)	14,119	78.9	129.4	2001.6	28.7	1984.7
Multiple myeloma and immunoproliferative neoplasms (C88,C90)	6,550	77.7	233.0	1995.1	9.7	1996.0
All other and unspecified malignant neoplasms (C17,C23-C24,C26-C31,C37-C41,C44-C49,C51-C52,C57-C60,C62-C63,C66,C68-C69,C73-C80,C97)	51,498	78.3	596.0	1997.0	35.1	1998.7

Table 2

No. of deaths and weighted sample means, by medical condition, 2019

Medical condition	n_deaths	age_death	n_hcpcs	vint_hcpcs	n_drug	vint_drug
In situ neoplasms, benign neoplasms and neoplasms of uncertain or unknown behavior (D00-D48)	8,746	81.4	684.7	1997.4	17.6	1989.7
Anemias (D50-D64)	658	84.4	219.8	1996.7	24.1	1983.3
Diabetes mellitus (E10-E14)	59,894	78.3	307.0	1997.2	43.0	1999.1
Parkinson's disease (G20-G21)	31,130	82.5	194.6	1997.9	18.6	1988.8
Alzheimer's disease (G30)	118,213	87.1	137.2	1996.5	3.0	1998.7
Acute rheumatic fever and chronic rheumatic heart diseases (I00-I09)	167	85.2	149.0	1997.0	6.3	1955.9
Acute myocardial infarction (I21-I22)	76,863	80.4	145.0	1996.9	5.0	1984.2
Other acute ischemic heart diseases (I24)	460	78.0	146.1	1997.3	6.0	1992.3
All other forms of chronic ischemic heart disease (I20,I25.1-I25.9)	161,111	83.4	203.8	1998.3	15.9	1985.2
Heart failure (I50)	76,565	85.5	209.9	1998.8	26.4	1984.0
All other forms of heart disease (I26-I28,I34-I38,I42-I49,I51)	108,978	83.1	275.8	1998.7	32.1	1987.9
Essential hypertension and hypertensive renal disease (I10,I12,I15)	26,649	83.5	98.4	1996.1	62.7	1984.2
Cerebrovascular diseases (I60-I69)	127,627	83.7	352.4	1997.5	11.1	2000.1
Atherosclerosis (I70)	1,227	88.1	250.3	1998.1	6.0	1993.5
Other diseases of arteries, arterioles and capillaries (I72-I78)	3,803	82.2	486.9	1996.1	7.8	1999.3
Other disorders of circulatory system (I80-I99)	154	73.9	396.4	1998.2	12.8	1981.3
Influenza (J09-J11)	452	80.7	40.7	1993.5	4.0	1994.6
Pneumonia (J12-J18)	33,272	83.4	94.6	1993.2	51.1	1980.0
Emphysema (J43)	2,057	77.2	141.6	1994.0	11.1	1987.3
Other chronic lower respiratory diseases (J44,J47)	123,851	80.1	145.3	1994.7	26.8	1990.3
Pneumonitis due to solids and liquids (J69)	12,544	84.4	55.0	1994.2	7.4	1958.6
Other diseases of respiratory system (J00-J06,J30- J39,J67,J70-J98)	33,364	80.4	324.8	1995.9	87.3	1978.9
Peptic ulcer (K25-K28)	342	78.5	62.9	1998.5	18.8	1983.5
Hernia (K40-K46)	22	82.1	74.0	1996.8	3.0	1967.7
Other chronic liver disease and cirrhosis (K73-K74)	7,735	73.5	95.7	1996.2	4.3	1979.2
Cholelithiasis and other disorders of gallbladder (K80-K82)	430	84.4	173.0	1994.9	1.2	1986.5
Renal failure (N17-N19)	38,359	81.2	138.2	1996.9	8.8	2003.3
Congenital malformations, deformations and chromosomal abnormalities (Q00-Q99)	22	65.5	693.0	1996.9	21.0	1979.7

Table 3

Estimates of parameters of variants of eq. (1):

$$\ln(age_death_{cs}) = \beta_1 \ln(n_hcpcs_{cs}) + \beta_2\, vint_hcpcs_{cs} + \beta_3 \ln(n_drug_{cs}) + \beta_4\, vint_drug_{cs} + \gamma \ln(n_deaths_{cs}) + \alpha_c + \delta_s + \varepsilon_{cs}$$

Column	1	2	3	4	5		6	7	8	9	10
Model	**Regressor**	**Estimate**	**Std. Err.**	**Z**	**Pr > |Z|**		**2013-2019 change in regressor mean (Δ)**	**effect type**	**effect (estimate * Δ)**	**Chi-Square**	**Pr > ChiSq**
1	$\ln(n_hcpcs_{cs})$	0.0254	0.0077	3.29	0.0010		0.115	hcpcs	0.0029	10.82	0.0010
2	$vint_hcpcs_{cs}$	0.0027	0.0006	4.74	<.0001		2.700	hcpcs	0.0072	22.44	<.0001
3	$\ln(n_drug_{cs})$	0.0088	0.0021	4.19	<.0001		0.134	drug	0.0012	17.54	<.0001
4	$vint_drug_{cs}$	0.0004	0.0001	4.02	<.0001		4.500	drug	0.0018	16.18	<.0001
5	$\ln(n_hcpcs_{cs})$	-0.0227	0.0107	-2.12	0.0340		0.115	hcpcs	0.0082	29.10	<.0001
	$vint_hcpcs_{cs}$	0.0040	0.0008	5.07	<.0001		2.700				
6	$\ln(n_drug_{cs})$	0.0081	0.0024	3.41	0.0007		0.134	drug	0.0015	14.44	0.0001
	$vint_drug_{cs}$	0.0001	0.0001	0.90	0.3655		4.500				
7	$\ln(n_hcpcs_{cs})$	-0.0237	0.0108	-2.19	0.0285		0.115	hcpcs	0.0064	19.55	<.0001
	$vint_hcpcs_{cs}$	0.0034	0.0007	4.55	<.0001		2.700				
	$\ln(n_drug_{cs})$	0.0043	0.0021	2.01	0.0444		0.134	drug	0.0011	8.06	0.0045
	$vint_drug_{cs}$	0.0001	0.0001	1.17	0.2410		4.500				
								total	0.0075	27.43	<.0001

Table 4

Estimates of parameters of variants of eq. (2):

$$\ln(avg_cost_{st}) = \rho_1 \ln(n_hcpcs_{st}) + \rho_2\ vint_hcpcs_{st} + \rho_3 \ln(n_drug_{st}) + \rho_4\ vint_drug_{st} + \delta_s + \alpha_t + \varepsilon_{st}$$

Column	1	2	3	4	5	6		7	8	9	10	11
Model	**Medicare Part**	**Regressor**	**Estimate**	**Std. Err.**	**Z**	**Pr > |Z|**		**2013-2019 change in regressor mean (Δ)**	**effect type**	**effect (estimate * Δ)**	**Chi-Square**	**Pr > Chi Sq**
8	B	$\ln(n_hcpcs_{cs})$	-0.3103	0.1795	-1.73	0.0839		0.115	hcpcs	-0.0358	2.99	0.0839
9	B	$vint_hcpcs_{cs}$	-0.0409	0.0241	-1.70	0.0896		2.700	hcpcs	-0.1104	2.89	0.0896
10	B	$\ln(n_drug_{cs})$	-0.2693	0.1075	-2.50	0.0123		0.134	drug	-0.0361	6.25	0.0123
11	B	$vint_drug_{cs}$	-0.0034	0.0044	-0.76	0.4459		4.500	drug	-0.0153	0.58	0.4459
12	B	$\ln(n_hcpcs_{cs})$	-0.1181	0.1975	-0.60	0.5500		0.115	hcpcs	-0.1236	3.43	0.0640
		$vint_hcpcs_{cs}$	-0.0406	0.0238	-1.71	0.0881		2.700				
		$\ln(n_drug_{cs})$	-0.2617	0.0987	-2.65	0.0081		0.134	drug	-0.0326	1.27	0.2594
		$vint_drug_{cs}$	0.0006	0.0058	0.11	0.9122		4.500				
									total	-0.1562	5.65	0.0174
13	A	$\ln(n_hcpcs_{cs})$	-0.3348	0.1397	-2.40	0.0165		0.115	hcpcs	-0.0386	5.76	0.0165
14	A	$vint_hcpcs_{cs}$	0.0181	0.0310	0.59	0.5578		2.700	hcpcs	0.0489	0.35	0.5578
15	A	$\ln(n_drug_{cs})$	-0.2820	0.1089	-2.59	0.0096		0.134	drug	-0.0379	6.71	0.0096
16	A	$vint_drug_{cs}$	-0.0125	0.0063	-2.01	0.0449		4.500	drug	-0.0563	4.04	0.0449
17	A	$\ln(n_hcpcs_{cs})$	-0.1906	0.2416	-0.79	0.4300		0.115	hcpcs	0.0539	0.42	0.5190
		$vint_hcpcs_{cs}$	0.0280	0.0334	0.84	0.4016		2.700				
		$\ln(n_drug_{cs})$	-0.2039	0.1210	-1.68	0.0921		0.134	drug	-0.0725	2.88	0.0898
		$vint_drug_{cs}$	-0.0100	0.0079	-1.26	0.2082		4.500				
									total	-0.0186	0.05	0.8297

Appendix Table 1

No. of deaths and weighted sample means, by state, 2019

State	n_deaths	age_death	n_hcpcs	vint_hcpcs	n_drug	vint_drug
All states	**1,432,798**	**81.4**	**215.6**	**1997.4**	**20.7**	**1991.7**
Alabama	26,485	79.6	200.4	1997.1	20.8	1991.5
Alaska	142	80.1	126.7	1996.5	7.1	1995.5
Arizona	29,316	80.9	212.3	1997.3	20.3	1992.3
Arkansas	15,281	79.9	178.7	1997.1	17.5	1991.3
California	158,521	82.4	242.0	1997.7	21.8	1992.7
Colorado	17,195	81.8	196.2	1997.5	19.6	1992.5
Connecticut	14,487	83.8	192.0	1997.1	21.1	1991.5
Delaware	2,457	82.4	165.6	1996.6	14.7	1992.6
District of Columbia	91	87.0	219.1	1997.3	9.9	1995.5
Florida	115,845	81.4	243.0	1997.8	21.8	1992.5
Georgia	43,006	79.8	211.8	1997.5	20.6	1991.6
Hawaii	3,318	84.7	148.0	1996.7	14.4	1993.0
Idaho	5,040	82.0	157.4	1996.5	16.2	1991.9
Illinois	59,854	81.5	219.3	1997.2	20.0	1991.6
Indiana	33,939	80.8	200.2	1996.9	20.1	1991.2
Iowa	13,905	82.7	178.4	1996.6	18.7	1990.5
Kansas	12,062	81.9	186.4	1997.0	18.9	1990.6
Kentucky	22,715	79.7	191.0	1996.5	20.4	1991.5
Louisiana	21,346	80.1	194.4	1997.5	21.0	1992.4
Maine	5,156	81.4	158.1	1996.6	16.1	1991.0
Maryland	22,384	81.1	217.5	1997.6	20.1	1991.2
Massachusetts	28,755	82.6	205.7	1997.0	22.1	1991.1
Michigan	52,937	81.6	208.8	1996.9	20.2	1990.9
Minnesota	21,876	82.8	210.4	1997.2	19.2	1991.8
Mississippi	15,002	79.6	176.8	1997.0	18.6	1991.7
Missouri	32,282	81.1	201.3	1997.0	19.6	1990.1
Montana	2,340	82.9	146.4	1996.6	18.1	1991.8
Nebraska	6,639	82.7	177.2	1997.1	18.5	1990.8
Nevada	9,601	79.4	192.7	1996.9	18.7	1992.1
New Hampshire	3,890	82.6	162.5	1996.6	15.4	1991.2
New Jersey	40,802	82.6	223.4	1997.8	22.2	1990.5
New Mexico	6,188	81.5	171.6	1996.9	16.1	1991.1
New York	87,450	82.3	230.4	1997.5	23.8	1991.2
North Carolina	49,850	80.5	216.6	1997.3	20.6	1992.1
North Dakota	1,168	87.0	126.3	1997.5	12.3	1992.0
Ohio	65,706	81.2	215.6	1997.3	21.2	1991.1
Oklahoma	16,583	80.2	183.1	1997.4	17.9	1991.4
Oregon	17,612	81.7	188.1	1997.0	18.7	1990.9
Pennsylvania	73,692	82.1	232.9	1997.6	21.9	1991.5
Rhode Island	2,572	85.1	141.9	1996.5	13.1	1992.4
South Carolina	23,638	79.9	199.3	1997.0	19.3	1991.2
South Dakota	2,296	83.6	128.4	1996.8	11.8	1991.8

Appendix Table 1

No. of deaths and weighted sample means, by state, 2019

State	n_deaths	age_death	n_hcpcs	vint_hcpcs	n_drug	vint_drug
Tennessee	33,819	79.7	204.1	1997.2	20.1	1992.4
Texas	106,135	80.5	231.1	1997.9	21.4	1992.2
Utah	6,802	82.5	178.6	1997.2	17.6	1991.2
Vermont	824	83.6	115.7	1996.6	11.6	1993.4
Virginia	35,856	81.0	208.9	1997.2	19.8	1990.9
Washington	29,147	81.6	204.2	1997.3	19.0	1992.3
West Virginia	9,221	80.0	172.5	1996.9	17.8	1991.4
Wisconsin	27,000	82.3	199.4	1997.2	19.0	1990.9
Wyoming	570	81.0	102.6	1995.8	11.9	1991.9