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

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Extended 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[1] (fee-for-service) Part B (medical insurance) beneficiaries by physicians and other healthcare professionals, by service (HCPCS code),[2] 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)).[3]

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.[4] One indicator of this is interstate variation in the *number* of distinct HCPCS codes provided.[5] 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.[6] 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%)

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[1] In 2019, 61% of Medicare beneficiaries were enrolled in traditional Medicare; 39% were enrolled in Medicare Advantage (Neuman, Biniek, and Freed (2025)).

[2] 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).

[3] 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.

[4] 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."

[5] 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.

[6] 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.

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.

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.[7] 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.[8] 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.[9]

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[10] 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.

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[7] 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.

[8] 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.

[9] 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.

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

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 approved by the FDA. The relative mean vintage of treatments provided to treat different diseases also varied across states. Figure 2 shows the mean FDA approval years of drugs used to treat 2 medical conditions provided in 2019 by Medicare Part D, by state.

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[11]—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.

[11] 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.

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'."

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 3, 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.[12] As noted above, we will analyze the effect of four measures of medical care provision. According to Cubanski and Neuman (2023), in 2021,

[12] 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.

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.

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:

$$\ln(\text{age_death}_{cs}) = \beta_1 \ln(\text{n_hcpcs}_{cs}) + \beta_2 \text{vint_hcpcs}_{cs} + \beta_3 \ln(\text{n_drug}_{cs}) + \beta_4 \text{vint_drug}_{cs} + \gamma \ln(\text{n_deaths}_{cs}) + \alpha_c + \delta_s + \varepsilon_{cs} \quad (1)$$

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.[13] 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)).

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.

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

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.[14]

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

[14] 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.

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 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

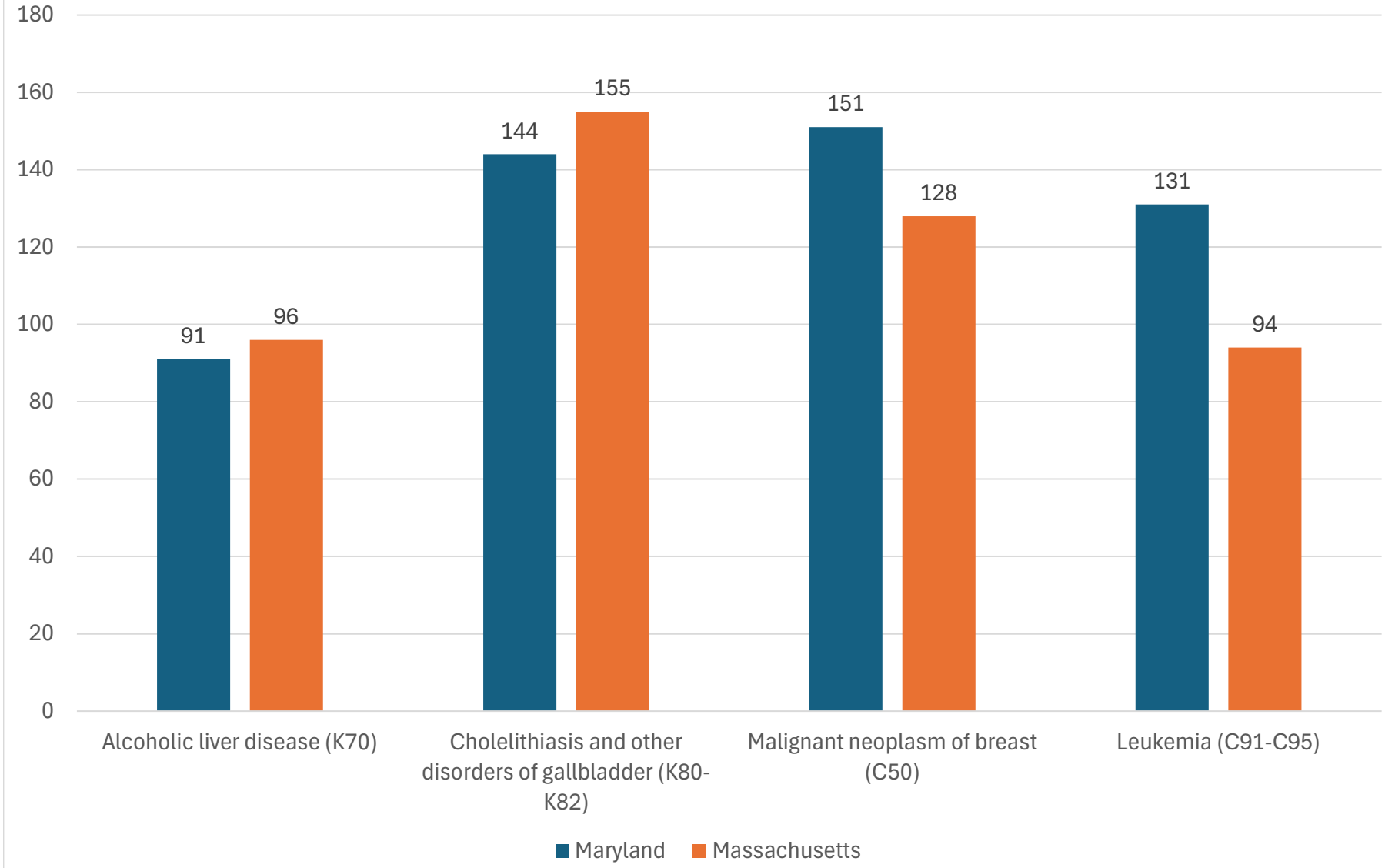
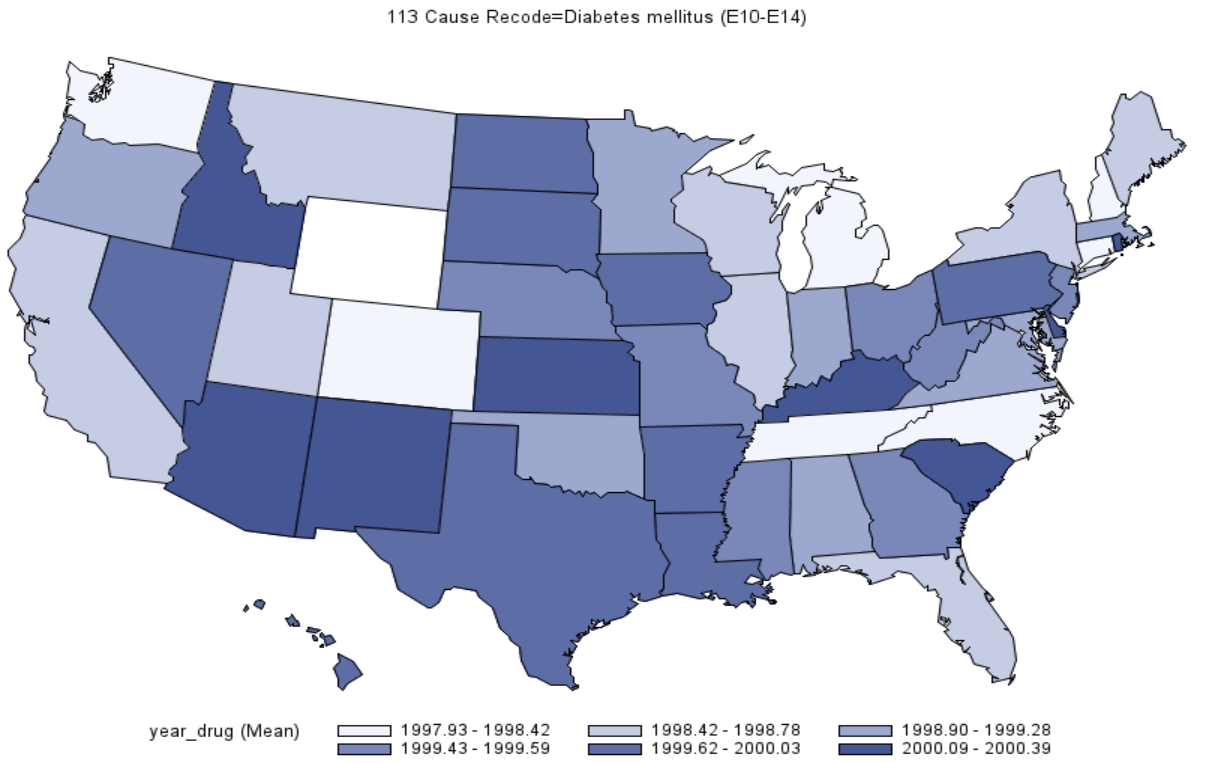


Figure 2

Mean FDA approval years of drugs used to treat 2 medical conditions provided in 2019 by Medicare Part D, by state



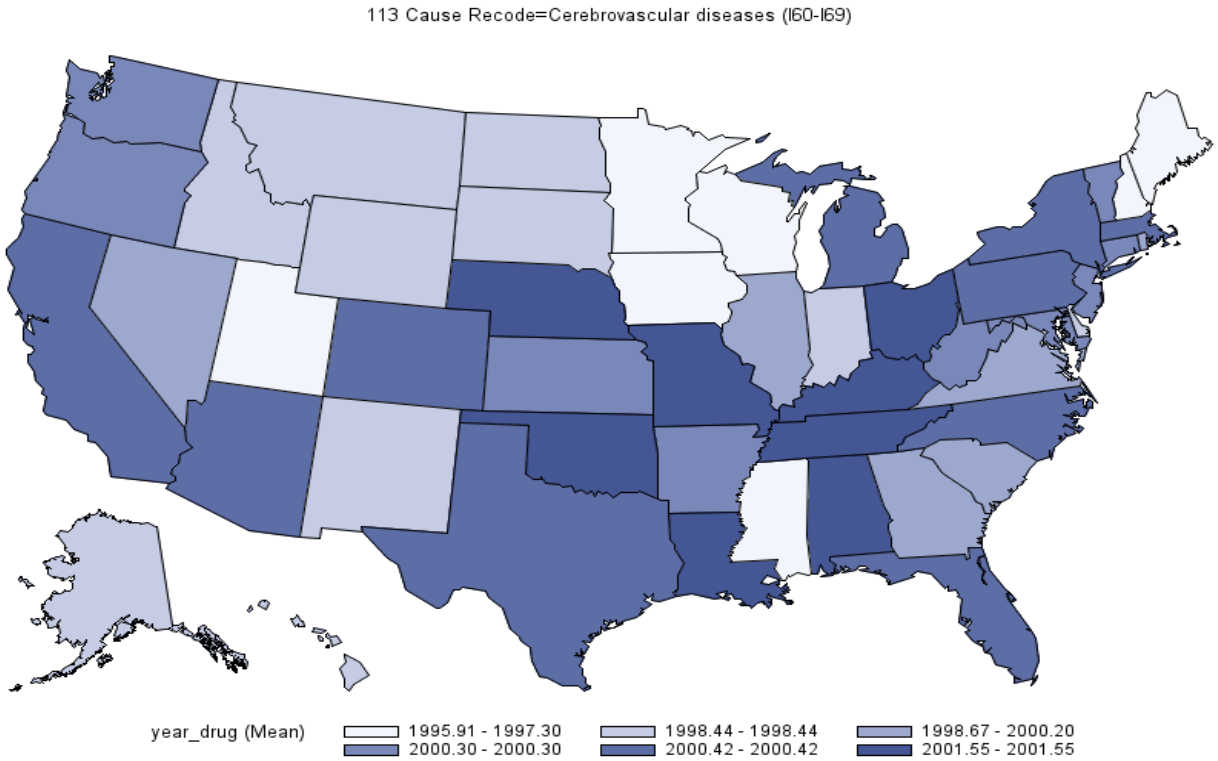
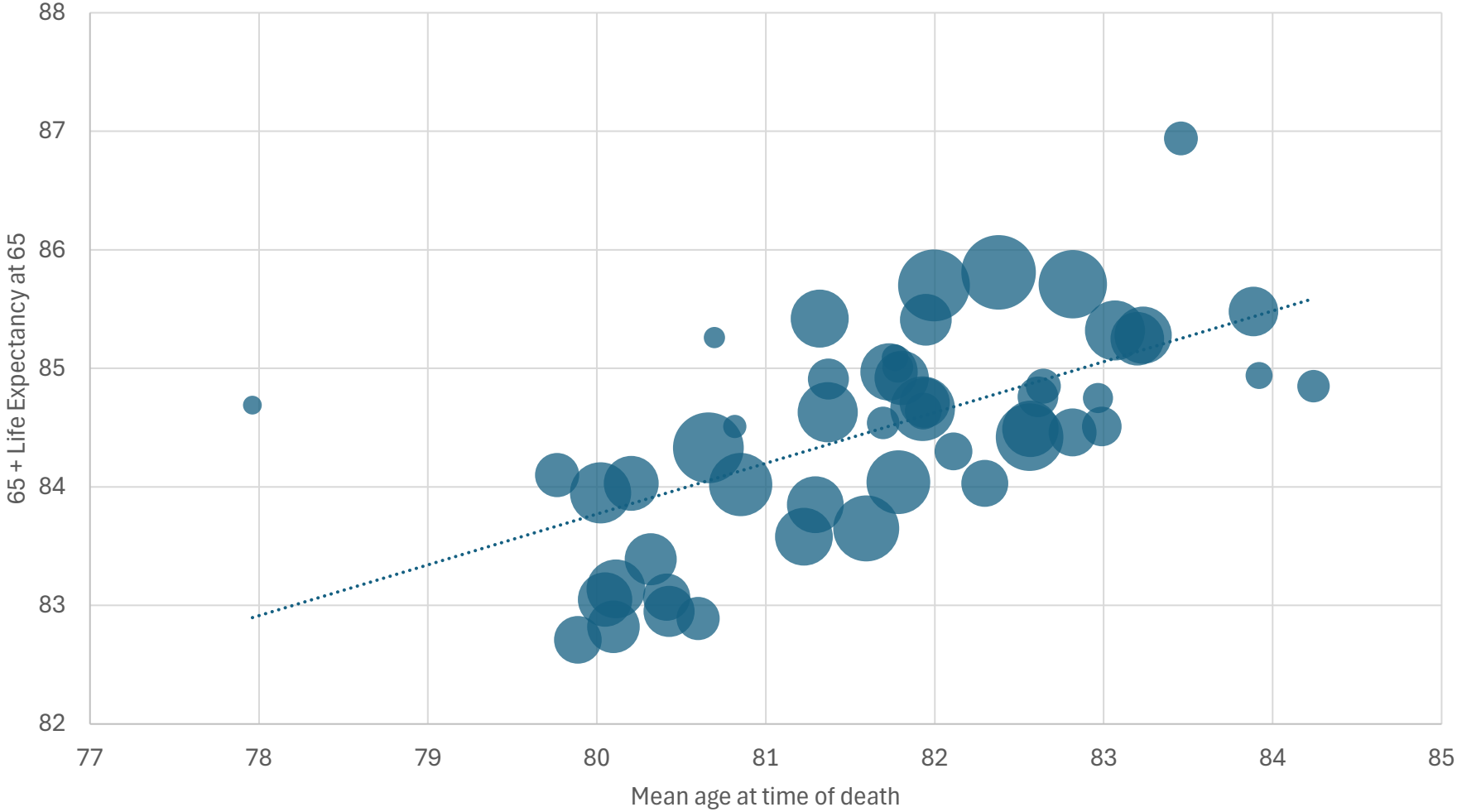


Figure 3
Correlation across states between
mean age at time of death of elderly (age 65 and over) decedents and
(65 + life expectancy at 65), 2019



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