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Distribution of Lifetime Medicare Taxes and Spending by Sex and by Lifetime Household Earnings

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Note

Numbers in the text, tables, and figures may not add up to totals because of rounding.

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Abstract

For any socioeconomic group, the consequences of changing Medicare depend on the distribution of taxes paid to and benefits received from the system in place. However, the few studies that have estimated that distribution offer conflicting views. To estimate the distribution of Medicare taxes and spending, I use a rich data set with information on beneficiaries' lifetime earnings and annual Medicare spending. In contrast with earlier studies, my data set includes more recent cohorts of beneficiaries. Here I project the distribution of Medicare taxes and spending on the basis of administrative earnings data as well as demographic and economic projections from the Congressional Budget Office's long-term microsimulation model.

This study's main analysis focuses on men born in the 1950s. For beneficiaries with higher lifetime household earnings, both lifetime Medicare taxes and lifetime spending (always understood herein to be net of premiums unless stated otherwise) are greater. Lifetime spending net of taxes, however, is about the same across quintiles except for being much lower for people in the highest quintile of lifetime household earnings. Those estimates and information on earnings suggest that lifetime Medicare spending net of taxes makes up a smaller share of lifetime individual earnings for beneficiaries with higher lifetime household earnings. That pattern also holds for women of the 1950s cohort. For younger cohorts, between the lowest and highest quintiles of lifetime household earnings, I expect the difference in net lifetime spending as a share of lifetime earnings to be larger.

Keywords: distribution; Medicare

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1. Introduction

In the coming decades, federal spending for Medicare—the largest federal health care program—is expected to grow faster than the economy. In fiscal year 2016, the Medicare program spent almost $600 billion on benefits for about 57 million people who are at least 65 years old, are disabled, or have end-stage kidney disease (CBO 2017). Medicare spending will increase from about 4 percent of gross domestic product (GDP) in 2016 to almost 7 percent in 2046 (CBO 2016b). That mounting fiscal pressure has prompted policymakers to consider measures to slow the program's growth. How such measures affect beneficiaries in different socioeconomic groups depends on the distribution of taxes paid to and benefits received from the current Medicare system by each group. However, the few studies that have estimated that distribution offer conflicting views. This study incorporates new estimates of the distribution of Medicare spending across beneficiaries with different lifetime household earnings for beneficiaries age 65 or older who were born in the 1950s.

Through its components, Medicare offers the following benefits:

- Part A (Hospital Insurance) covers inpatient services, care in skilled nursing facilities, home health care, and hospice care.
- Part B (Medical Insurance) covers mainly services from physicians, other practitioners, and hospitals' outpatient departments.
- Part D (prescription drug coverage) covers a prescription drug benefit, which private insurance plans administer.

In fiscal year 2016, over 40 percent of total Medicare spending was for Part A services, under 45 percent for Part B services, and under 15 percent for Part D services (CBO 2017). That spending includes payments to Medicare Advantage (or Part C) plans.

The distribution of Medicare—or how lifetime Medicare spending net of lifetime contributions to Medicare varies across beneficiaries of different socioeconomic status (SES)—is unclear. Contributions to the Medicare system come mainly from Medicare taxes, Medicare premiums, and other sources (mostly transfers from the general fund).[1] This analysis, however, does not consider transfers from the general fund and other financing sources, which together finance about 45 percent of Medicare spending in 2015 (CBO 2016b). Costs consist mostly of payments for Medicare-covered services. This study uses lifetime household earnings as the measure of SES. Taxes increase almost proportionally with earnings, and people with higher earnings pay higher premiums.[2] However, whether beneficiaries with higher lifetime household earnings also have higher lifetime spending is unclear. For example, beneficiaries with higher lifetime household earnings might have lower lifetime spending because of better health status, resulting in lower annual spending. Alternatively, they might have higher lifetime spending because of higher annual spending associated with greater demand for health care services or longer life expectancy.

Net lifetime spending (herein, always considered as lifetime spending net of premiums and dedicated Medicare taxes unless stated otherwise) across cohorts could vary because of changes such as economic growth or the overall growth in total Medicare spending. Under the existing system, people working today contribute to a significant portion of the benefits that current beneficiaries receive. With Medicare growing faster than the economy, the mismatch between what each cohort pays into and receives from the system will grow. Projected net

[1]The general fund is one category of federal funds in the government's accounting structure. The general fund records all revenues and offsetting receipts not earmarked by law for a specific purpose as well as all spending financed by those revenues and receipts.
[2]Premiums for Parts B and D are higher for beneficiaries with higher income. Medicare taxes consist mostly of payroll taxes, which are a fixed percentage of earnings, so people with higher earnings would pay more in Medicare taxes. The current rate for Medicare payroll taxes (both the employee and employer shares) is 2.9 percent. (Starting in 2013, an additional tax of 0.9 percent is applied to income higher than $200,000 for individuals and $250,000 for married people.)

lifetime Medicare spending across cohorts also will change. If either economic growth or spending growth affects different SES groups differently, the distribution of Medicare across cohorts would change.

Using the Congressional Budget Office's long-term budget model (CBOLT), my analysis of the distribution of Medicare by lifetime household earnings focuses on future beneficiaries. Each individual in the sample from CBOLT has a complete history of earnings and household structure, compiled from Social Security administrative data and from CBO's long-term projections, allowing me to calculate lifetime household earnings at the individual level. The calculation of annual taxes and spending, along with projected life spans, allow me to examine how lifetime taxes and spending vary with lifetime household earnings.[3]

Medicare taxes consist mostly of payroll taxes from both employers and employees. (The rest, a very small share, comes from income taxes on Social Security benefits.) For the 1950s cohort, the administrative data include most of the earnings over beneficiaries' lifetimes. I calculate annual payroll taxes from the history of individual earnings and tax rates. (Income taxes on Social Security benefits are based on projected incomes and Social Security benefits for people age 65 or older.)

To calculate annual spending for beneficiaries age 65 or older who were born in the 1950s, I first estimate the relationship between the primary insurance amount (PIA)—a measure of lifetime individual earnings—and annual Medicare spending. I do so by constructing a longitudinal sample of Medicare enrollees age 65 or older from the 1994–2005 National Health

[3]Before 2013, basic demographic information (such as age and sex), annual earnings, and Social Security benefits claiming are from Social Security administrative data; household structure and additional individual characteristics are imputed. Starting in 2013, all individual characteristics are projected using CBO's long-term projections. My analysis incorporates the long-term demographic, economic, and budgetary assumptions that underlie CBO's 2016 long-term budget projections (CBO 2016b).

Interview Survey (NHIS) linked to Medicare and Social Security administrative files.[4] Next, I project annual spending for Medicare beneficiaries age 65 or older who were born in the 1950s in CBOLT given that estimated relationship between PIA and annual Medicare spending along with information from CBOLT (that is, the PIA estimated from the data on individual earnings and the projections of other individual characteristics).

The main discussion describes distributional results for men born in the 1950s. The focus is on men because the projection method is better at capturing the relationship between SES and Medicare spending for that group. The projections of Medicare spending are based on the estimated historical relationship between my measure of individual earnings (PIA) and Medicare spending. In the past, men were more likely to work than women, so a measure of individual earnings better corresponds to SES for men. I also present some results for younger cohorts, but those results are qualitative because of the considerable uncertainty inherent in longer-term projections.

Both lifetime Medicare taxes and lifetime spending are greater for male beneficiaries born in the 1950s with higher lifetime household earnings. (Lifetime taxes are greater for higher-SES groups because Medicare taxes consist mostly of payroll taxes, which are a fixed share of annual earnings; higher life expectancy explains more than half of the difference in lifetime spending between the lowest and highest SES groups.) Lifetime spending net of taxes, however, is about the same across quintiles except for people in the highest quintile of lifetime household earnings, where it is much lower. Combining those estimates with information on earnings, I find that lifetime Medicare spending net of taxes makes up a smaller share of lifetime individual

[4]Most people become eligible for Medicare when they turn 65. Disabled people generally become eligible 24 months after they qualify for benefits under Social Security's Disability Insurance program. Currently, about 85 percent of Medicare beneficiaries are age 65 or older.

earnings for beneficiaries with higher lifetime household earnings. That pattern also holds for women born in the 1950s.

I expect the distribution of Medicare to change across cohorts: Between people in the lowest and highest quintiles of lifetime household earnings, the difference in net lifetime Medicare spending measured as a share of lifetime earnings is larger for younger cohorts. That pattern holds for both men and women.

2. Literature Review

Three studies that examined the distribution of Medicare reached different conclusions because of differences in methods used. Permanent income is the relevant measure of SES to evaluate the distribution of a publicly funded program such as Medicare because SES is closely related to the how much beneficiaries contribute in taxes. Using permanent income also captures lifetime resources available to beneficiaries. The measure of permanent income chosen affects Medicare's estimated progressivity. In those studies, Medicare is said to be progressive if beneficiaries with higher SES have lower net lifetime Medicare spending.[5] Whereas two studies that used individual-level measures of permanent income found Medicare to be progressive, one study used an average over individuals as a measure of permanent income and found Medicare to be neutral.

Bhattacharya and Lakdawalla (2006) and Rettenmaier (2012) found Medicare to be progressive by using individual-level measures of permanent income. Bhattacharya and Lakdawalla used education as a measure of permanent income. That study focused on the distribution of lifetime spending received from Medicare Part A and lifetime Medicare taxes paid to finance those expenditures. The authors found that annual Part A spending tends to decline

[5]In the discussion of previous studies, the calculation of lifetime spending does not include premiums.

with education. Under a reasonable set of assumptions on the spending growth of Part A and the discount rate, lifetime Part A spending usually also declines with education. Because lifetime Medicare taxes tend to increase with education level, lifetime Part A spending net of Medicare taxes almost always declines with education on average.

Using lifetime individual earnings as a measure of permanent income, Rettenmaier also concluded that Medicare is progressive. But the study reached different conclusions on how lifetime spending varies with permanent income. Rettenmaier measured lifetime individual earnings as the present value of earnings starting at age 40 as compiled from Social Security administrative records.[6] An eight-year history of annual Medicare spending from Medicare administrative records also is available for each individual in the sample.[7] Whereas Bhattacharya and Lakdawalla found a negative SES gradient of lifetime spending on Part A, Rettenmaier showed that lifetime spending on both Part A and Part B increases with lifetime earnings and that the positive gradient is steeper for Part B.[8] The positive gradient of lifetime taxes and premiums with respect to lifetime earnings, however, is steeper than that of lifetime spending. Rettenmaier concluded that both Parts A and B of Medicare are progressive but suggested that the Medicare program is less progressive than Bhattacharya and Lakdawalla found.

McClellan and Skinner (2006) found that the distribution of Medicare is neutral across ZIP codes with different average income. Instead of estimating Medicare spending for individuals of different SES, they estimated average Medicare spending for beneficiaries residing in ZIP codes with different average income. Those authors found that the relationship between

[6]A present value is a single number that expresses a flow of past and future earnings, spending, or taxes in terms of an equivalent lump sum received or paid at a specific time. The value depends on the rate of interest, known as the discount rate, used to translate past and future cash flows into current dollars at that time.

[7]Outside the eight-year window, annual Medicare spending is imputed based on the observed relationship between the measure of lifetime earnings and annual spending in the sample.

[8]Those results from Bhattacharya and Lakdawalla (2006) correspond to the assumption of 3 percent discount rate, the same assumption used in Rettenmaier (2012).

ZIP code average income and annual Medicare spending changes: In 1987, annual Medicare spending increased with ZIP code average income; in 2001, annual spending declined with ZIP code average income.[9] Because of differences in life expectancy, both lifetime spending and lifetime taxes (including payroll taxes, premiums, and federal income taxes attributed to Part B) increase with ZIP code average income, and lifetime spending net of taxes is similar across beneficiaries residing in ZIP codes with different average income.

My study differs from previous studies in how I evaluate the distribution of Medicare. Following the approach of previous studies, I estimate how lifetime Medicare taxes, premiums, and spending vary with respect to a measure of permanent income. My evaluation of the distribution of Medicare, however, is based on how net lifetime spending varies as a share of lifetime earnings rather than how such spending varies.[10]

This study contributes to the literature in several ways. First, I project the distribution of Medicare for beneficiaries born in 1950 or later, accounting for observed and projected changes in population demographics and labor market outcomes as well as changes in Medicare policy. Life expectancy and individual earnings are the most important factors in evaluating the distribution of Medicare. CBOLT starts with a random sample from the administrative earnings records that include basic demographic information, earnings data from 1951 to 2012, and information on Social Security benefit claiming. For the 1950s cohort, most of their earnings histories are observed in the data. Other individual characteristics, such as marital status and

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[9]In contrast, De Nardi and others (2015) found a positive gradient of annual Medicare spending with respect to individual income by using the Medicare Current Beneficiary Survey, 1996–2010. The choice between an individual and an average measure of income could affect the income gradient of annual Medicare spending.

[10]Analysts have used different measures to evaluate the distribution of policies. In discussing expenditures, progressivity is usually defined as a lower level of benefits for people of higher SES; in discussing tax policies, progressivity is usually defined as higher average tax rates for people of higher SES (Steuerle 2008). The measure I use to evaluate the distribution of net Medicare spending is more closely related to the latter definition. Examining net benefits as a share of lifetime earnings also allows me to account for economic growth when comparing the distribution of Medicare across cohorts.

education, are imputed for those individuals. The projections of individual demographic characteristics and labor market outcomes start in 2013. The projection of life expectancy affects my analysis mostly by affecting the number of years that beneficiaries receive Medicare benefits and therefore lifetime spending: The increasing differences in life expectancy across SES would lead to a steeper SES gradient of lifetime spending.[11] Labor market outcomes directly affect the calculation of lifetime taxes: Increasing earnings inequality observed in the administrative data for the 1950s cohort would lead to a steeper SES gradient of lifetime taxes. This analysis also reflects current Medicare policies. For example, before 1994, only earnings below the taxable maximum are included for calculating Medicare payroll taxes.[12] The elimination of the taxable maximum for Medicare payroll taxes starting in 1994 increases lifetime taxes, thus reducing net lifetime spending, for current and future beneficiaries of higher lifetime household earnings.

Second, my measure of permanent income, PIA, is a more complete measure of individual permanent income than ZIP code average income and educational attainment. Those two measures serve as proxies for lifetime earnings, and analysis based on those measures leaves out important variations in Medicare spending with respect to permanent income. The variation in ZIP code average Medicare spending with respect to ZIP code average income could capture higher payments to providers (for example, higher salaries to doctors) in areas with higher average incomes or other geographic variation in Medicare spending independent of the variation in individual income.[13] The variation in Medicare spending with respect to education could

[11]For the 1950s cohort, my results are less sensitive to the projections of other demographic characteristics, such as education or marital status, because those characteristics are observed in the data or the distribution of those characteristics are observed in history. Even if those characteristics continue to evolve after the last sample year, the rates of change in those characteristics are likely to be very small for the older population.

[12]Before 1991, Medicare and Social Security payroll taxes had the same taxable maximum. Between 1991 and 1993, the taxable maximum for Medicare was much higher than that for Social Security.

[13]Though findings from papers in the literature disagree on the relative magnitude, most of those authors found that a significant portion of the geographic variation in Medicare spending is due to variation in practice patterns rather than beneficiary characteristics (see, for example, Finkelstein, Gentzkow, and Williams [2016] and Sheiner [2014]).

capture more than the direct effect of permanent income. For example, higher educational attainment might reflect greater cognitive skills, which could affect Medicare spending by affording better access to appropriate care and improved health outcomes independent of permanent income.

The PIA is closely related to the measure of lifetime earnings that Rettenmaier (2012) used, and it is more appropriate for understanding the existing Medicare system. My measure captures almost the complete history of individual earnings rather than individual earnings starting at age 40, as Rettenmaier did. Similar to the approach in Rettenmaier (2012), I assign beneficiaries to different quintiles of lifetime household earnings by sex and single year of birth. Because my measure captures a significant portion of resources over a lifetime and reflects the ranking of each beneficiary within his or her cohort, the relationship between my measure and annual Medicare spending is more likely to be consistent across cohorts.[14]

Third, the panel structure of both my survey sample and CBOLT allows me to account for persistence in individual Medicare spending and taxes, which affects the distribution of lifetime outcomes. If an annual outcome persists, any shock to that annual outcome and any later shocks would accumulate. Therefore, accounting for persistence in an annual outcome could increase the dispersion in the corresponding lifetime outcome across individuals. Previous studies used the averages of annual outcomes over subgroups of beneficiaries to impute lifetime

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In addition, the variation in ZIP code average income might not be the same as the variation of ZIP code average income of people age 65 or older because of the difference in the income sources between people age 65 or older and those under age 65.

[14]In contrast, the variation in annual spending with respect to either ZIP code average income or education is more likely to reflect contemporaneous factors specific to each cohort. Although ZIP code average income removes idiosyncratic shocks to individual earnings, it reflects the effect of aggregate economic shocks in a particular period. Therefore, I would expect the relationship between average ZIP code income and average ZIP code Medicare spending to change. I also would expect changes in the education gradient of Medicare taxes and spending. Educational attainment and the relationship between educational attainment and earnings have changed dramatically over the last three decades (Lemieux 2006), and those changes are expected to continue. Changes in the distribution of education lead to changes in the composition of beneficiaries within each education category, which affect the education gradient of Medicare spending; changes in the relationship between education and earnings directly affect the education gradient of Medicare taxes.

spending and taxes without accounting for persistence in those outcomes within each individual.[15] The panel structure of my survey data allows me to estimate the persistence in Medicare enrollment and spending. (Previous studies estimated the average spending by SES, but I separately model enrollment and spending to allow for different relationships between SES and those outcomes and for different patterns of persistence.) CBOLT allows me to incorporate the persistence in those annual outcomes into the projections of lifetime spending; the calculation of lifetime taxes incorporates the persistence in individual earnings. Because my analysis compares average lifetime outcomes across several groups of beneficiaries rather than the dispersion across individuals, accounting for the persistence in spending and taxes has only a small effect on my main results.

Finally, I contribute to the literature by estimating the SES gradient of Medicare spending by using a sample that includes more cohorts of beneficiaries and more recent cohorts of beneficiaries. The three studies discussed above use information on Medicare spending for samples of beneficiaries born in the 1910s or 1920s; my study uses Medicare spending for a sample of beneficiaries born between 1905 and 1940. The program has evolved greatly in both its size and services provided. In 1970, when the 1905 cohort turned 65, average Medicare spending per beneficiary was about $1,500, of which more than 70 percent was spent on hospital services; in 2005, when the 1940 cohort turned 65, that average was about $7,000, of which only about 55 percent was spent on hospital services.[16] Because of changes to the Medicare program, the relationship between individual characteristics (including measures of SES) and spending

[15]Rettenmaier (2012) accounted for the persistence in Medicare spending and earnings when he used actual data in his simulation. Outside the sample period, he did not account for the persistence in annual outcomes.
[16]The values are based on data from the Centers for Medicare & Medicaid Services, Medicare & Medicaid Statistical Supplement (2013 edition), http://go.usa.gov/x3xyH. The dollar values are deflated to 2009 dollars by using the GDP price index.

probably also changed. My use of a longer panel of cohorts allows me to incorporate estimates that better reflect the experience of current beneficiaries.

This study has several important limitations. (See the final section for more details.) First, in projecting distribution of Medicare, I anticipated that the rate of change in annual spending as PIA increases, as observed in the survey data, would continue in my projection period.[17] Continued changes in the Medicare system, such as medical technology and payment rules, would probably change that relationship. Second, my estimates of contributions to Medicare include only premiums and Medicare taxes as financing sources. In 2015, premiums and Medicare taxes financed about 60 percent of Medicare spending, whereas other sources (mostly transfers from general fund financed the rest (CBO 2016b).[18] Including those other sources would increase lifetime taxes (thus lowering net lifetime spending) for all beneficiaries, but probably by more for those with higher lifetime household earnings because individual income taxes are the largest component of general revenues and they are more progressive than payroll taxes (CBO 2016a).[19] Third, my projection incorporates the assumption that Medicare will pay for all the benefits as specified under the current rules.[20] Medicare taxes paid by workers and Medicare premiums paid by enrollees are projected to make up a declining share of Medicare revenues, so transfers from the general fund and other financing sources will become more important for financing Medicare and thus for evaluating the distribution of Medicare. Despite

[17]Although the relationship between PIA and individual Medicare spending is fixed in the projection period, the level of Medicare spending per beneficiary is projected to increase. The projected rate of that growth is determined by the growth of potential GDP (or maximum sustainable output of the economy) and excess cost growth of Medicare (CBO 2016b). Appendix A further describes the projections of total Medicare spending.

[18]Other financing sources for Medicare include interest from the trust funds and amounts paid by states from savings on Medicaid's prescription drug costs.

[19]How including transfers from the general fund would affect the distribution of Medicare would depend on the method for allocating deficits and transfers from the general fund to all federal programs. The final section includes a more detailed discussion.

[20]The amount of dedicated taxes used to finance almost all Part A spending plus the remaining balance in the Part A trust fund is projected to fall below Part A spending in 2025 (CBO 2017)—that is, when someone born in the 1950s is between the ages of 65 and 75 years.

those limitations, my estimates provide the most detailed and up-to-date modeling of the distribution of Medicare.

3. Projection Method

In this study, I use CBOLT to project the distribution of net lifetime Medicare spending by lifetime household earnings quintile. Net lifetime Medicare spending reflects individual contributions to the Medicare system and benefits from it. Lifetime household earnings, a household-level measure that reflects the sharing of resources in a household, quantifies permanent income in the distributional analysis.

CBOLT is a microsimulation model that simulates the transitions of individual demographic characteristics, labor market outcomes, and benefit claiming starting from a sample of individual earnings records between 1951 and 2012 from the Social Security Administration. In CBOLT, earnings before 1984 are capped at the taxable maximum for the Social Security payroll taxes. For data between 1984 and 2012, individual earnings include wages, tips, and self-employment income from Form W-2.[21] Other demographic characteristics, such as education and marital status, are imputed for individuals up to 2012. Beyond 2012, the demographic and labor market transitions are simulated based on CBO's long-term economic and demographic projections as well as a set of parameters estimated using historical data. (Appendix A further describes CBOLT's imputation and projection methods.)

With projected life expectancy for each individual in CBOLT, I can examine how lifetime taxes and spending vary with lifetime household earnings because I can calculate annual

[21]Olsen and Hudson (2009) further described the types of earnings included in the Social Security administrative earnings records.

taxes and spending, as well as lifetime household earnings, for each individual. (Figure 1 shows the components of the projections.)

CBOLT calculates annual Medicare taxes and spending on the basis of demographic characteristics and labor market outcomes. Using information on individual earnings and tax rates, I calculate a history of annual Medicare taxes for each individual. (Most earnings for the 1950s cohort are observed in the data, so my calculation of Medicare payroll taxes and lifetime household earnings relies mostly on the observed data.) The projection of annual Medicare spending is based on projected individual characteristics and on the relationship between those characteristics and annual spending on Parts A and B estimated from survey data. (My analysis focuses on the 1950s cohort, so I calculate annual spending starting in 2015, when people born in 1950 turned 65.)

3.1. Lifetime Household Earnings

Using the history of individual earnings and household structure, I calculate lifetime household earnings for each individual in CBOLT. Lifetime household earnings are calculated as the present value of the sum of annual earnings over the lifetime of each individual in the household. For years in which the individual is married, the annual household earnings are the sum of earnings from both the individual and the spouse, adjusted for economies of scale.[22] For years in which the individual is single, widowed, or divorced, the annual household earnings include the earnings from that individual only.

Using earnings capped at the Social Security taxable maximum before 1984 could affect my measure of permanent income and lifetime household earnings—and therefore the ordering of individuals. People with earnings above the taxable maximum are more likely to be in the

[22]The sum of earnings is divided by 1.5692, which is roughly $2^{0.65}$. Recommended by the National Research Council (1995), that adjustment factor is used to calculate per capita household earnings, accounting for shared resources between spouses.

highest quintile of lifetime household earnings, so I expect the effect of capped earnings on the assignment of individuals to quintile groups and the effect on my results to be small.

3.2. Individual Medicare Taxes and Premiums

Different parts of Medicare are financed in different ways. Spending on Part A is financed by dedicated sources of income, which consists mostly of a payroll tax (amounting to 2.9 percent of all earnings).[23] (For many participants, that rate was much lower in earlier years, even zero before 1966.) Premiums paid by beneficiaries finance about a quarter of spending on Part B, and transfers from the general fund cover the rest. Enrollees' premiums under Part D are set to cover about a quarter of the cost of the basic prescription drug benefit (although many low-income enrollees pay no premiums), and transfers from the general fund cover most of the rest. In 2015, Medicare taxes financed about 40 percent of spending on Medicare, about 15 percent came from beneficiaries' premiums, and the rest came from other sources (mostly transfers from the general fund); in 2046, those shares are projected to be 21 percent and 18 percent, respectively (CBO 2016b).

In my analysis, contributions to Medicare include taxes dedicated to the Medicare program and premiums on Parts A, B, and D. Most Medicare taxes are paid by beneficiaries before they enroll in Medicare, and premiums are paid after they enroll. For the 1950s cohort, in addition to legislated tax rates, lifetime taxes are calculated mostly on the basis of observed earnings; income taxes on benefits are based on the projected Social Security benefits and

[23]My analysis of Medicare taxes also includes a portion of the federal income taxes paid on Social Security benefits, which constitutes a small share of total Medicare taxes. Starting in 2013, the payroll taxes also include a 0.9 percent tax on income over $200,000 (or $250,000 for married couples). Those additional taxes for high earners would have a very small effect on the distribution of Medicare for the 1950s cohort because most of their payroll taxes were paid before 2013.

projected individual incomes.[24] (CBOLT does not impute or project individual income taxes for other financing sources.) For individual premiums, I distribute the projected total premiums equally among all Medicare beneficiaries. That method abstracts from the fact that out-of-pocket costs of Medicare premiums vary across beneficiaries.[25]

Using earnings capped at the Social Security taxable maximum before 1984 does not affect my calculation of payroll taxes because before 1991, Medicare payroll taxes applied only to earnings below the taxable maximum.

3.3. Individual Medicare Spending

I project annual Medicare spending from projected individual characteristics in CBOLT and an estimation of how those individual characteristics relate to annual enrollment in Parts A and B and to annual spending on Parts A and B. To do so, I used a sample of fee-for-service (FFS) Medicare beneficiaries in the NHIS linked to administrative data as well as projected growth in total spending.[26] Modeling the enrollment decision is important for estimating the distribution of Medicare because that decision affects how long people's lifetime enrollment in Medicare lasts, thereby affecting Medicare spending and premiums. The enrollment decision also could affect Medicare taxes if eligible people prefer working longer to receive employer-sponsored insurance coverage and delay Medicare enrollment.

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[24]Payroll taxes are calculated based on observed earnings before 2013; they are projected starting in 2013 on the basis of projected earnings and current tax rates. For most people born in 1950 or later, income taxes on Social Security benefits are projected because those benefits are received at older ages.

[25]A small portion of beneficiaries pay Part A premiums. In addition, some high-income beneficiaries, about 6 percent of Medicare beneficiaries in 2015, pay income-related premiums for Part B services in addition to the regular premiums (Cubanski and Neuman 2015); Medicaid paid premiums for Part A and Part B for under 20 percent of Medicare beneficiaries in 2009 (CBO 2013). Incorporating those differences in the actual costs of Medicare premiums to beneficiaries would probably increase lifetime spending more for those with lower lifetime household earnings than for those with higher lifetime household earnings.

[26]For the 1950s cohort, my calculation of annual Medicare spending is not very sensitive to the projections of individual characteristics, such as education or marital status, because those characteristics or their distributions are observed in history for most of their lifetime. Even if those characteristics continue to evolve after the last sample year, those characteristics are not likely to change much for the older population.

My projection of individual Medicare spending includes the part that can be predicted from a set of individual characteristics and the part that cannot. The first component incorporates the assumption that the variation in annual Medicare expenditures per beneficiary with respect to individual characteristics in the future will be the same as that of FFS payments to providers for services covered by Parts A and B, as estimated from historical data in the linked NHIS. For the second component, a random number is drawn for each beneficiary in each projection year to determine the amount of spending that cannot be explained by any of those individual characteristics.[27] The predicted individual annual spending (or the sum of those two components) is adjusted by an annual multiplicative factor such that the total spending matches CBO's projections of total Medicare spending.[28]

To fully incorporate the correlation between lifetime household earnings and lifetime spending in my distributional analysis, I would need to include lifetime household earnings in my regression analysis of annual Medicare spending by individuals. However, because I know of no data set that contains complete histories of both earnings and Medicare spending, I use the PIA from Social Security's administrative records, which is available in the linked NHIS data. The PIA is calculated from the average of the highest 35 years of taxable earnings. (People with no PIA value on their records are included in the analysis and assigned a separate category.) The PIA correlates closely with lifetime individual earnings.[29] Because people tend to marry those

[27]See Appendix B for more on the sample construction and the estimation method. To avoid outliers for predicted Medicare spending, the random draws are restricted to be within two standard deviations of the mean.
[28]In addition to direct payments to providers for services covered by Parts A and B, CBO's projections of total Medicare expenditures also include payments to Medicare Advantage plans, spending on Part D benefits, and direct payments to providers not related to specific claims.
[29]For individuals eligible for Social Security retirement benefits, average indexed monthly earnings (AIME) are calculated based on the highest 35 years of taxable earnings. (*Taxable earnings* refer to earnings below a certain threshold, which are included in the calculation of Social Security payroll taxes.) The indexed earnings reflect the adjustment to account for the growth of wages. For a worker with fewer than 35 years of positive earnings, AIME is the total earnings divided by the number of months in 35 years; for a worker with more than 35 years of positive earnings, only 35 years of the highest earnings is used in calculating AIME. (The exception includes people eligible

with similar characteristics, lifetime individual earnings also should correlate with lifetime household earnings.

To minimize the bias in my estimated distribution of Medicare by lifetime household earnings, I choose PIA as the measure of permanent income. The following analysis includes PIA measures for Social Security beneficiaries whose eligibility is based on their own work histories. Using a measure other than lifetime household earnings in the regression analysis would bias my estimated distribution of Medicare spending because that estimate does not capture all the variation in lifetime household earnings and, hence, the variation in annual spending with respect to lifetime household earnings. Instead, that estimate captures only the variation in annual spending with respect to the measure used in the regression analysis. The magnitude of bias will be smaller if the variation in that measure is more closely related to the portion of variation in lifetime household earnings that predicts variation in annual Medicare spending. PIA is a good choice for my analysis because in the CBOLT sample PIA and lifetime household earnings are strongly correlated, especially for men (see Table 1).[30]

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for Social Security disability benefits before reaching their full retirement age. For those beneficiaries, the number of annual earnings included in the calculation of AIME depends on the age at which the individual first becomes eligible for disability benefits.) PIA is a strictly increasing function of AIME that gives higher return to people with lower lifetime earnings. Because the function is strictly increasing, the transformation from AIME to PIA does not change the ordering of beneficiaries; that is, if one beneficiary has higher AIME than another beneficiary born in the same year, he or she also has a higher PIA than the other beneficiary. Therefore, the assignment into quintiles based on PIA by sex and birth year is identical to that of AIME.

[30]Two earlier studies provide biased estimates of the distribution of Medicare for reasons discussed in the paragraph. Lacking the data available for this research, NAS (2015) and Steuerle and Quakenbush (2015) examined the distribution of Medicare across beneficiaries of different SES. NAS (2015) presented the distribution of Medicare with respect to lifetime income; Steuerle and Quakenbush (2015) presented lifetime taxes and spending for beneficiaries with different hypothetical earnings histories, focusing less on distribution and more on changes over long periods in benefits and taxes for hypothetical individuals at similar relative positions in the lifetime earnings distribution. The imputations of annual Medicare spending in NAS (2015) were based on the variation of spending with respect to a rich set of individual characteristics, including education and health status. That relationship, however, does not include lifetime income. Thus, the distributional effects in NAS (2015) included only the variation in annual spending with respect to the set of individual characteristics specified in the regression model. Steuerle and Quakenbush (2015) assumed that annual Medicare spending is the same for all beneficiaries, so the estimated lifetime Medicare spending is completely driven by the overall growth of Medicare expenditures and the assumption of lifetime expectancy, but not by the variation in annual spending across individuals. In the appendix of

4. Projected Annual Medicare Spending

The projected relationship between lifetime household earnings and annual Medicare spending depends on the relationship between lifetime household earnings and PIA as well as the relationship between PIA and annual spending. The demographic information and labor market outcomes in CBOLT allow me to calculate both an individual PIA and lifetime household earnings for each individual. Using CBO's projections of individual life expectancy and total Medicare spending, I project annual Medicare spending on the basis of the estimated historical relationship between individual characteristics (including individual PIA) and annual Medicare spending on Parts A and B. To do so, I used a sample of beneficiaries age 65 or older who were born between 1905 and 1940 from the NHIS linked to administrative records from the Centers for Medicare & Medicaid Services and the Social Security Administration. That historical relationship is estimated separately by sex and age group for both Medicare enrollment and spending. I generally find a significant relationship between PIA and Medicare enrollment and spending, and the magnitude of variation tends to be greater at younger ages. (Appendix B describes the sample construction and the estimation.)

4.1. Relationship Between PIA and Lifetime Household Earnings in CBOLT

As discussed earlier, using PIA to project spending is appropriate for estimating the distribution of Medicare by lifetime household earnings if PIA is closely related to lifetime household earnings. In CBOLT, both the quintile of lifetime household earnings and the quintile of PIA are assigned separately by sex and single-year birth cohort by using a sample of individuals who live at least to age 45. PIA and lifetime household earnings are correlated for people born in the

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an earlier study (Steuerle and Quakenbush 2012), they did show how that assumption was altered by using average spending by age group, but the basic limitation still holds.

1950s who live at least to age 65 in the CBOLT sample, and the correlation is stronger for men (Table 1).

The main discussion will focus on men born in the 1950s because of the stronger relationship between PIA and lifetime household earnings for that group. That relationship indicates a smaller discrepancy in my method, which uses PIA in the estimation step and the other measure in the projection step. The weaker relationship between PIA and lifetime household earnings for women probably reflects the weaker labor force attachment and marriage patterns for the 1950s cohort. Women in that cohort are less likely to work and therefore less likely to have a PIA. Men in that cohort tend to be the major income source for the households, and the correlation between a measure of individual earnings, or PIA, and a measure of household earnings, or lifetime household earnings, is stronger for men.

My method's validity also relies on a stable distribution of PIA between cohorts in the survey sample and the 1950s cohort in the projections, which is less likely to hold for women. Since the time of the cohorts in my survey sample (1905–1940), women have participated in the labor force at higher rates. That change would result in changes in the distribution of PIA, which could lead to changes in the relationship between PIA and annual spending. In analyzing the 1950s cohort, I assumed the same relationship between PIA (along with other individual characteristics) and annual spending as estimated from a sample of beneficiaries born between 1905 and 1940, so changes in women's labor force participation would violate that key assumption underlying my projection method.

4.2. Relationship Between PIA and Annual Medicare Spending in CBOLT

For my sample of male beneficiaries born in the 1950s, the relationship between PIA and annual spending is generally not monotonic, but it tends to have a negative gradient (Figure 2A). For men under age 80, average annual Medicare spending is the highest for those in the lowest PIA quintile and similar for those with a higher PIA; for men age 80 or older, average Medicare spending declines between the first and second quintiles before rising monotonically with PIA.

For women born in the 1950s, average spending generally declines monotonically with PIA (Figure 2B). In addition, variation in average spending by PIA tends to be smaller for older women. For example, among women ages 65–69, average spending of those in the first PIA quintile is about 60 percent higher than for those in the fifth PIA quintile; among women age 80 or older, the magnitude of variation in annual spending across the PIA quintiles is within 10 percent.

5. Lifetime Medicare Taxes and Spending by Lifetime Household Earnings

Lifetime Medicare taxes and spending vary by quintile of lifetime household earnings for beneficiaries born in the 1950s who live at least to age 65. The main discussion focuses on men. For each person in the CBOLT sample, I calculate the present values of lifetime Medicare taxes and spending on the basis of projected annual taxes and spending, in addition to projected life expectancy. The annual amounts are adjusted for inflation to 2016 dollars by using the GDP deflator and discounted to age 65 by using the effective interest rate on all federal debt. (See Appendix A in CBO [2016b] for more on CBO's projections of interest rate.)

The analysis considers Medicare taxes, Medicare premiums, and Medicare spending. Medicare taxes consist of payroll taxes (both the employer's and employee's shares) and a portion of taxes paid on Social Security benefits. (The calculations do not include contributions to Medicare made from general fund.) Lifetime Medicare spending includes Medicare spending net of premiums paid to the government for beneficiaries at or after age 65.

5.1. Distribution of Medicare for Men Born in the 1950s

For men born in the 1950s, beneficiaries with higher lifetime household earnings have higher lifetime taxes (Figure 3). Lifetime taxes are about $15,000 for beneficiaries age 65 or older in the lowest quintiles of lifetime household earnings. For beneficiaries in the highest quintile of lifetime household earnings, lifetime taxes are about $270,000. Beneficiaries with higher lifetime household earnings have higher lifetime Medicare spending (Figure 3). Lifetime spending is about $165,000 for beneficiaries age 65 or older in the lowest quintile of lifetime household earnings, and it is about $305,000 for people in the highest quintile of lifetime household earnings.

Projected differences in life expectancy across quintiles of lifetime household earnings explain more than half of the difference in lifetime spending between the lowest and highest quintiles of lifetime household earnings. For men born in the 1950s, the difference in average life expectancy at age 65 between the lowest and the highest quintile is more than 6 years. To quantify the share of the difference in lifetime Medicare spending across quintiles of lifetime household earnings explained by the difference in life expectancy, I compare results from two model specifications: the model discussed above, which projects a lower rate of mortality for beneficiaries with higher lifetime earnings, and a model in which I project the same rate of mortality for all beneficiaries. Differences in mortality explain about half of the difference in lifetime spending between the lowest and highest quintiles of lifetime household earnings. (The rest of the difference can be explained by the projected variation in annual Medicare spending across quintiles and the differences in that relationship across different age groups.)

Lifetime spending net of taxes is similar for beneficiaries in the first and fourth quintiles, but it is much lower for those in the highest quintile (Figure 3). Lifetime Medicare spending net of taxes is about $150,000 for beneficiaries age 65 or older in the lowest quintile of lifetime household earnings and $35,000 for people in the highest quintile. The lack of progressivity, except for those with the highest SES, is consistent with the results in Rettenmaier (2012), which incorporates Medicare financing from general fund. Rettenmaier also found that most of the decline in net lifetime spending occurs between the top two deciles of lifetime earnings, which is driven by the much steeper SES gradient of lifetime taxes between those two groups. In other words, Medicare is roughly neutral for about 90 percent of the beneficiaries and progressive for 10 percent of the beneficiaries with the highest SES. Those results illustrate the pitfalls in interpreting social programs' distributional results on the basis of the difference in net benefits between the lowest and highest SES group while ignoring the SES gradient between those two extreme groups.

In my analysis, I evaluate the distribution of Medicare on the basis of the difference in net lifetime spending as a share of lifetime earnings. I find that measure to be lower for men born in the 1950s with higher lifetime household earnings, and the difference across quintiles is not driven by the highest SES group (Figure 4). Beneficiaries in different quintiles of lifetime household earnings pay similar shares of lifetime earnings for Medicare taxes over their lifetime, about 3 percent, because of the fixed rate of payroll taxes. Lifetime spending is a higher share of lifetime earnings for beneficiaries with lower lifetime household earnings: Lifetime spending is about 30 percent of lifetime earnings for beneficiaries in the lowest quintile of lifetime household earnings and less than 5 percent for those in the highest quintile.

5.2. Distribution of Medicare for Women Born in the 1950s

Several patterns in the distributional results for women born in the 1950s are likely to hold despite some issues with the projection method for women. The distributional results for women born in the 1950s might be less robust than those for men because of changes in women's labor force participation and earnings between the cohorts in my survey sample and the 1950s cohort.

Because of their longer projected life expectancy, women tend to have higher lifetime spending than men, but the difference in lifetime spending between the lowest and highest quintile is smaller for women (Figure 5). For the 1950s cohort, on average, women are expected to live 2.5 years longer than men at age 65. The difference in lifetime spending between the lowest and highest quintiles of lifetime household earnings is smaller than that for men because the difference in life expectancy across quintiles is projected to be smaller for women. For my sample of women born in the 1950s, the difference in life expectancy at age 65 between the lowest and highest quintiles of lifetime household earnings is more than 4 years; for the sample of men born in the 1950s, that difference is more than 6 years. Because of higher Medicare spending for older beneficiaries, on average, the difference in life expectancy between men and women leads to a significant difference in their lifetime spending.

Net lifetime Medicare spending as a share of lifetime earnings is lower for women born in the 1950s with higher lifetime household earnings (Figure 6). For beneficiaries in the lowest quintile of lifetime household earnings, lifetime spending is about 65 percent of lifetime earnings, compared with about 10 percent for beneficiaries in the highest quintile of lifetime household earnings.

5.3. Distribution of Medicare for Younger Cohorts

The distribution of Medicare is expected to change for younger cohorts, but considerable uncertainty exists with a longer projection horizon.

To examine how the distribution of Medicare changes across cohorts, I compare projected lifetime spending as a share of lifetime earnings for beneficiaries born in the 1950s, 1960s, and 1970s. The discussion focuses on lifetime spending because lifetime taxes are about 3 percent of lifetime earnings across quintiles of lifetime household earnings and birth cohorts because of the fixed payroll tax rate and because Medicare taxes in my analysis consist mostly of payroll taxes.

The difference in lifetime Medicare spending as a share of lifetime earnings between beneficiaries in the lowest and highest quintiles of lifetime household earnings is expected to be greater for younger birth cohorts. Faster growth in lifetime earnings for men with higher lifetime household earnings is the most important factor for explaining the increase in that difference for younger cohorts; for women, the most important factor is slower growth of lifetime spending for those with higher lifetime household earnings.

6. Discussion and Conclusion

My study complements and supplements earlier studies on the distribution of Medicare by taking advantage of a unique data set that links a measure of lifetime earnings with Medicare spending. When evaluating the distribution of public programs such as Medicare, researchers face the difficulty of measuring permanent income, and earlier studies reached different conclusions about the distribution of Medicare depending on the measure of permanent income used. This study improves on earlier studies by estimating the relationship between permanent income and spending by using more recent cohorts of beneficiaries and accounting for projected changes in population demographics when projecting the distribution of Medicare for current and future beneficiaries. Using lifetime household earnings as a measure of permanent income, I find that net lifetime spending as a share of lifetime earnings is lower for beneficiaries with higher lifetime household earnings.

My results are consistent with those of earlier studies that used an individual-level measure of permanent income (Bhattacharya and Lakdawalla [2006] and Rettenmaier [2012]), but they differ from those that use ZIP code average income as a measure of permanent income (McClellan and Skinner 2006). Using the same definition of progressivity as those earlier studies, I examine how net lifetime spending varies with my measure of permanent income. My measure of permanent income is similar to that in Rettenmaier (2012): lifetime household earnings versus lifetime earnings starting at age 40. My measure of taxes, however, is different from that of Rettenmaier: This study focuses on payroll taxes, whereas Rettenmaier also examined the portion of general fund used to finance Medicare. Despite those differences (in addition to the difference in sample period), the variation of net lifetime spending with respect to permanent income has similar patterns in this study and Rettenmaier: The level of net lifetime spending declines slightly with permanent income for most beneficiaries, with a much lower level for people with the highest level of permanent income, and a high level of lifetime taxes drives that large difference. As discussed in the results section, the lack of progressivity for men except for the highest SES group points to the importance of examining the entire distribution of SES when researchers analyze the distributional effects of social programs.

This study has several limitations. First, I do not consider the distribution of the general fund used to finance a portion of Medicare spending. Including transfers from the general fund would increase lifetime taxes (thus lowering net lifetime spending), but probably by more for beneficiaries with higher lifetime household earnings because income taxes are more progressive than payroll taxes. Those transfers may become increasingly important for financing Medicare because of the projected shortfall in the program. However, estimating how much each Medicare beneficiary contributes to the portion of the general fund that finances Medicare would require assumptions about the distribution of taxes, spending, and deficits across generations and across all government programs.

Second, my analysis excludes Medicare spending incurred before age 65 and excludes individuals who die before 65. For people who became Medicare beneficiaries before age 65 (by qualifying for Social Security Disability Insurance) and who live to at least age 65, my measures of net spending would include taxes, but not spending, before age 65. Because disabled individuals tend to have low SES and high levels of health care expenditures, including Medicare spending before age 65 in my analysis would probably have increased net lifetime spending by more for beneficiaries with lower lifetime household earnings. Individuals who die before age 65 are not included in the analysis; some of those people would have received Social Security Disability Insurance and Medicare during their lives and some would not have received benefits under those programs. Additional analysis is required to evaluate how including those two groups affects the progressivity of Medicare overall: Some low-SES individuals would have high levels of Medicare spending, and some low-SES individuals would have no spending.

Third, the projected distribution of Medicare spending incorporates the assumption of the same utilization patterns conditional on the set of characteristics for current and future beneficiaries as observed for my survey sample of FFS enrollees. Although I account for projected changes in the composition of beneficiaries in my projections, those changes also could change the relationship between individual characteristics and spending. One such change is the labor market attachment and outcomes of women. Women's participation in the labor force had been increasing steadily before flattening out starting in the 1990s, so future female workers will be more likely to have a PIA—and higher PIA value—than women in my sample. Such shifts in the labor market could change the relationship between quintile of PIA and demand for health care because of changes in the composition of women in each PIA quintile and the category of missing PIA. Higher labor force participation also could change women's marriage decisions and therefore the composition of women within each quintile of lifetime household earnings.

Changes in Medicare utilization patterns, medical technology, or payment rules also could change the relationship between individual characteristics and spending. With an increasing share of medical services being provided outside hospitals, spending on Part B services as a share of total spending on Part A and Part B has increased, from around 30 percent in the early 1980s to 48 percent in 2013. Such shifts in utilization patterns could affect the distribution of Medicare if the distribution of spending across those types of Medicare services varies by permanent income. Without a better understanding of the drivers—not just correlates—of Medicare spending, how those changes affect the projected distribution of Medicare is unclear.

Fourth, projected annual Medicare spending is based on the estimated relationship between PIA and direct payments to providers for Part A and Part B services that FFS enrollees receive. CBO's projections of total Medicare spending also include payments to Medicare Advantage plans (Part C), spending on Part D benefits, and indirect payments to providers and other program expenses. The analysis in this paper incorporates the assumption that the distribution of those types of spending is the same as that of the direct payments to providers for Part A and Part B services that FFS enrollees receive. But that assumption might be wrong. For example, the distribution of spending on Part D benefits could be different from spending on Part A and Part B services because of differences in the cost-sharing rules and in the composition of enrollees.

Fifth, to project individual premiums, I distribute the projected total premiums equally among all Medicare beneficiaries. That method abstracts from the fact that the out-of-pocket costs of Medicare premiums vary across beneficiaries and tend to be higher for higher-income households. Incorporating those differences in the actual costs of Medicare premiums to beneficiaries would probably increase the difference in lifetime spending across quintiles of lifetime household earnings.

Finally, my measure of Medicare spending does not account for welfare gains or losses. The value of Medicare to beneficiaries might differ from what Medicare paid for medical services. McClellan and Skinner (2009) used a utility-based approach to value Medicare and argued that Medicare is more progressive after incorporating the insurance value of the program. In their model, beneficiaries of higher SES value Medicare more because they tend to live longer and demand more medical services; beneficiaries of lower SES value Medicare more because their access to health insurance is more limited without Medicare. I do not try to account for the insurance value of Medicare in my distributional analysis because of insufficient evidence from the literature to support such evaluation.

Figure 1.
The Congressional Budget Office's Long-Term Projections of the Distribution of Medicare for the 1950s Cohort

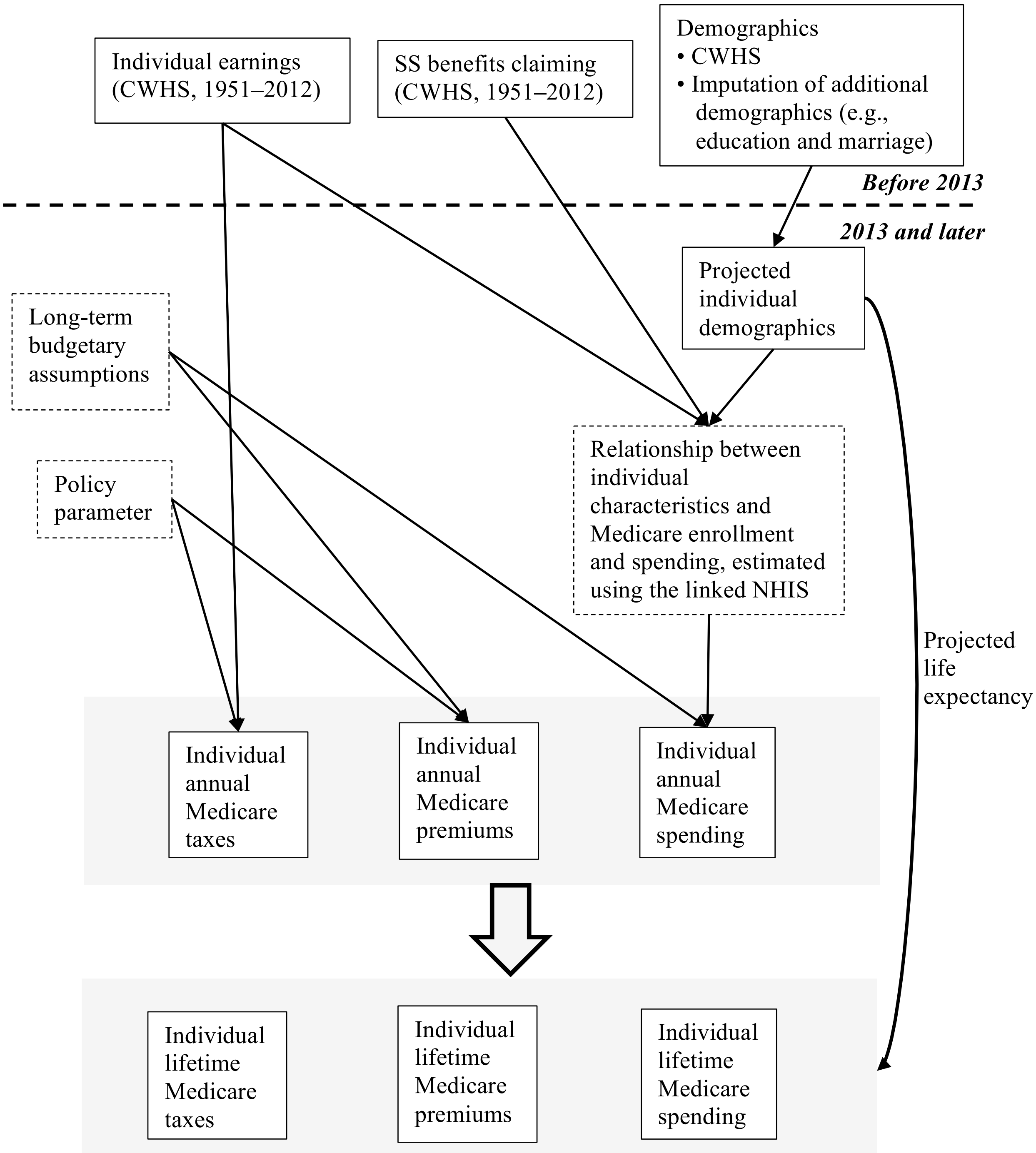
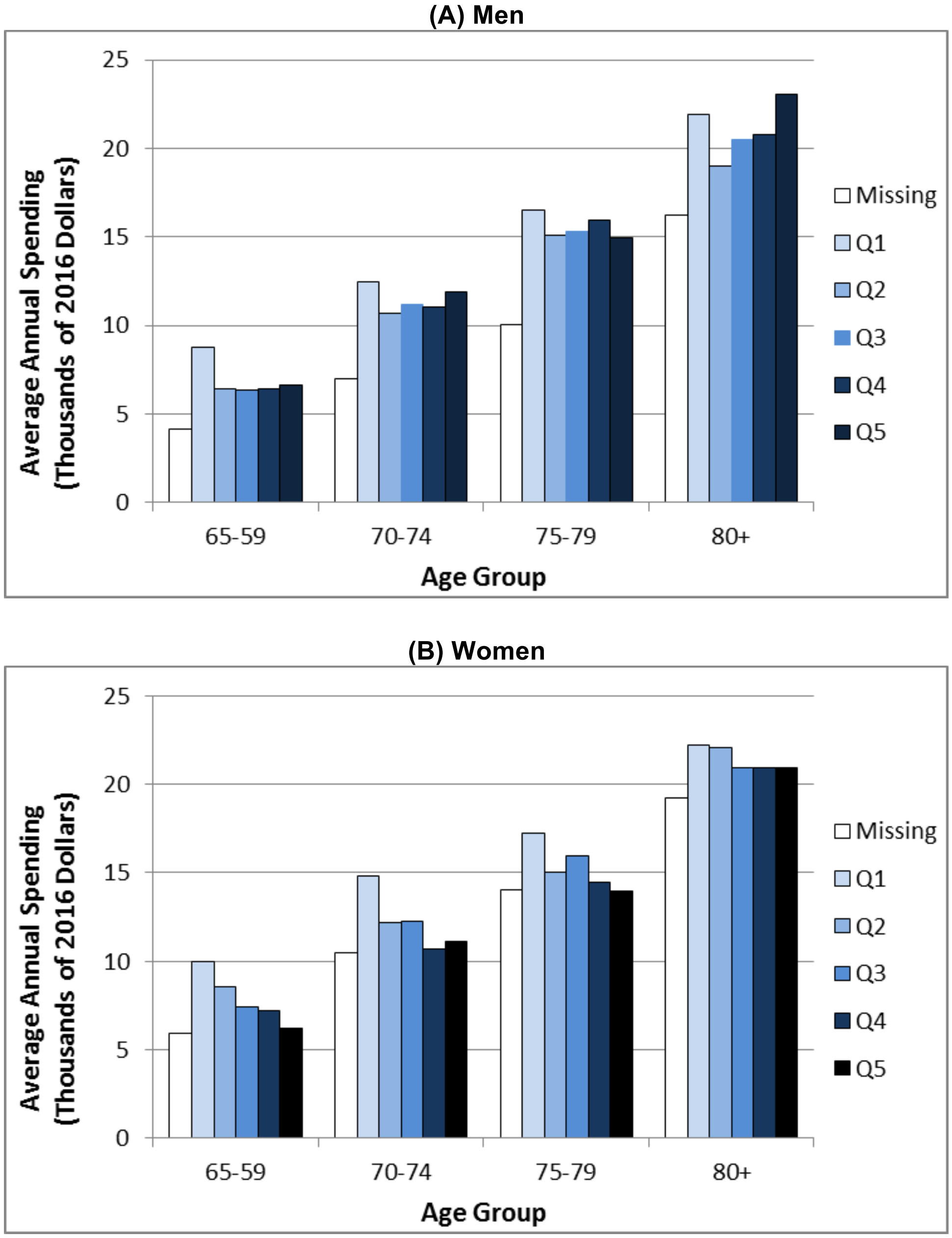
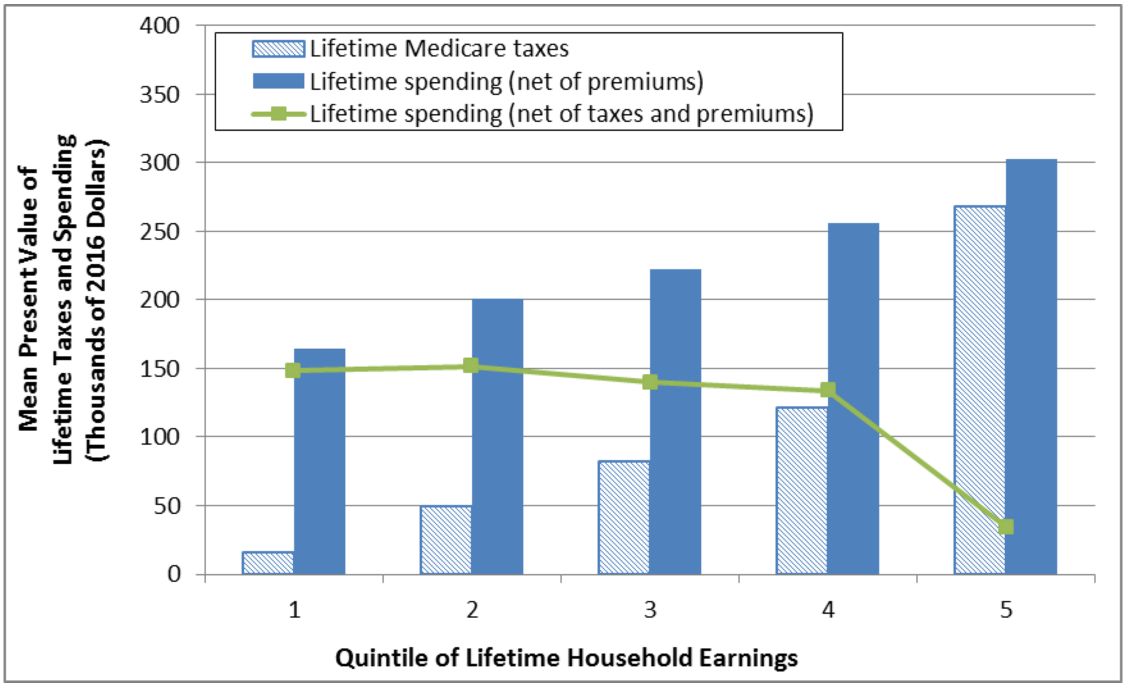


Figure 2.
Average Annual Medicare Spending by Age, Sex, and Primary Insurance Amount Quintile for Beneficiaries Born in the 1950s



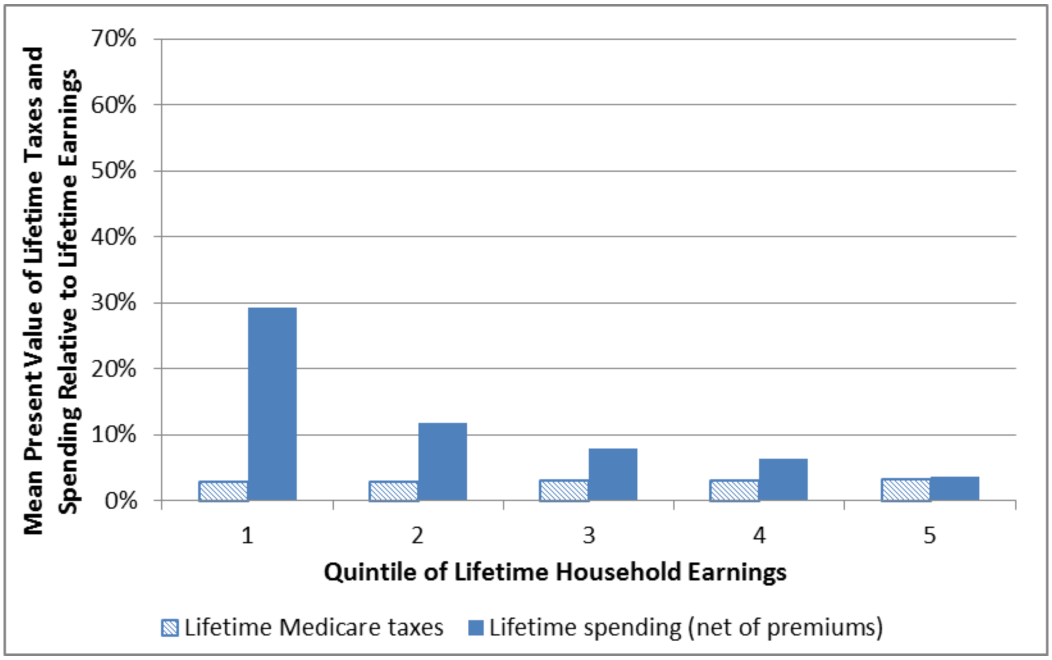
Estimates are based on the projected annual Medicare spending for beneficiaries age 65 or older born in the 1950s in the CBOLT sample. The dollar amounts are adjusted for inflation to 2016 dollars by using the gross domestic product deflator and discounted to age 65 by using the effective interest rate on all federal debt.

Figure 3.
Mean Lifetime Medicare Taxes and Spending (Net of Premiums) by Quintile of Lifetime Household Earnings, Men



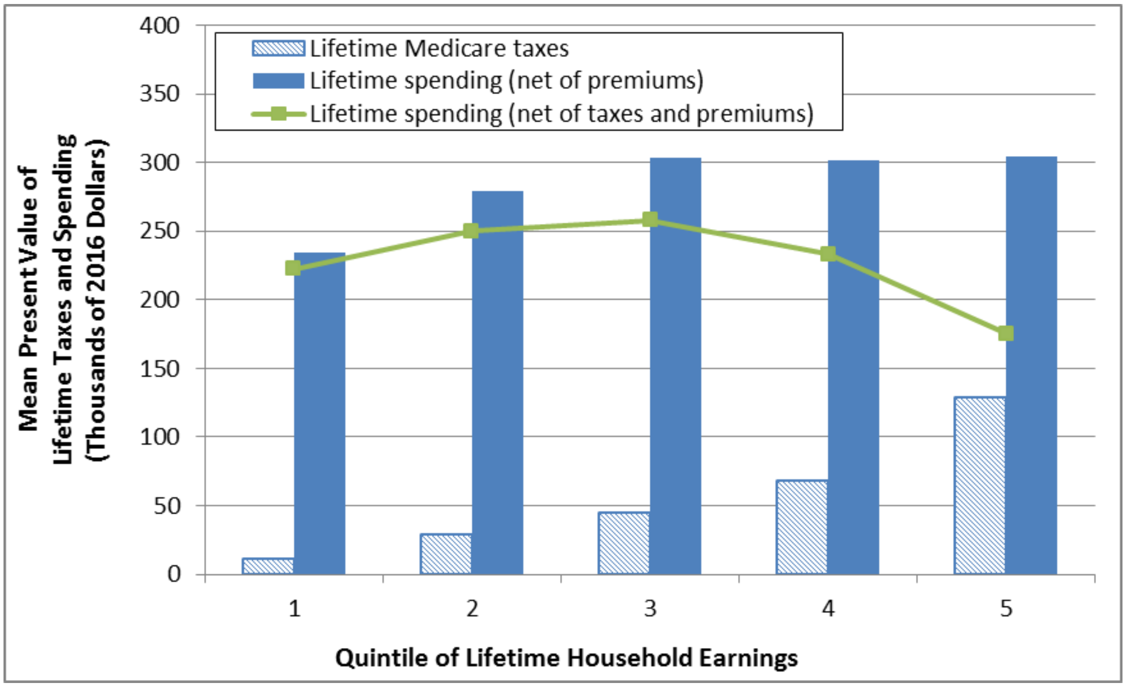
Amounts shown are lifetime Medicare taxes and spending for male beneficiaries age 65 or older born in the 1950s who live at least to age 65. Lifetime Medicare taxes include mostly payroll taxes paid to the program. Payroll taxes consist of the employer's and employee's shares combined. Lifetime Medicare spending includes Medicare spending for beneficiaries at or after age 65 (net of premiums that beneficiaries paid to the government). The dollar amounts are adjusted for inflation to 2016 dollars by using the gross domestic product deflator and discounted to age 65 by using the effective interest rate on all federal debt.

Figure 4.
Mean Present Value of Lifetime Medicare Taxes and Spending (Net of Premiums) as a Share of Lifetime Earnings by Quintile of Lifetime Household Earnings, Men



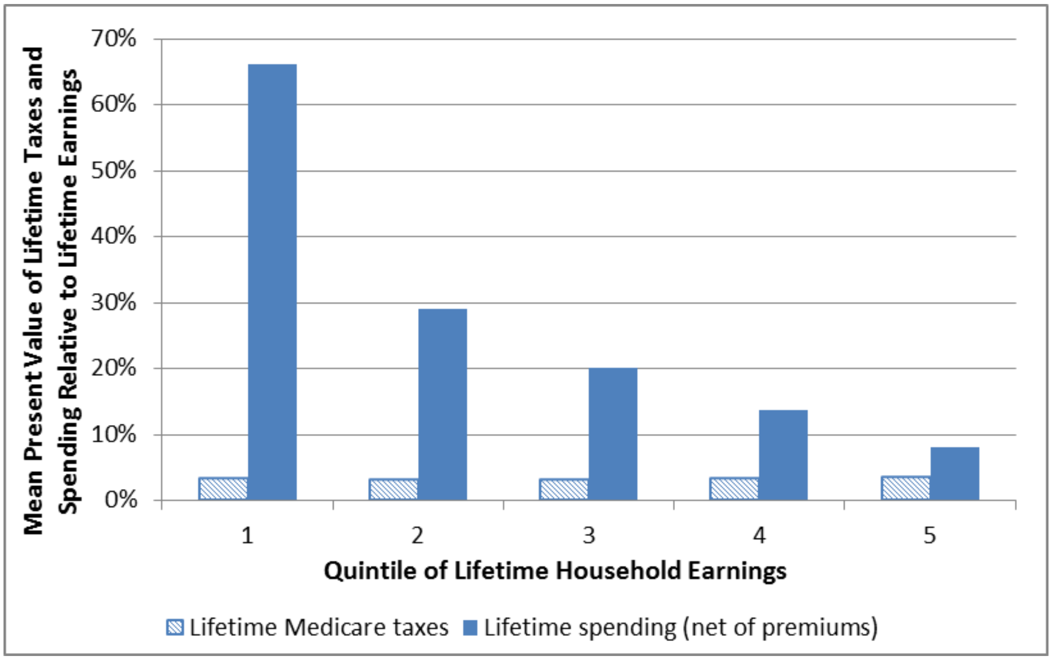
Amounts shown are ratios of lifetime Medicare taxes and spending to lifetime earnings for male beneficiaries age 65 or older born in the 1950s who live at least to age 65. Lifetime Medicare taxes include mostly payroll taxes paid to the program. Payroll taxes consist of the employer's and employee's shares combined. Lifetime Medicare spending includes total Medicare spending for beneficiaries at or after age 65 (net of premiums that beneficiaries paid to the government). Lifetime earnings are the present value of individual earnings over a lifetime.

Figure 5.
Mean Lifetime Medicare Taxes and Spending (Net of Premiums) by Quintile of Lifetime Household Earnings, Women



Amounts shown are lifetime Medicare taxes and spending for female beneficiaries age 65 or older born in the 1950s who live at least to age 65. Lifetime Medicare taxes include mostly payroll taxes paid to the program. Payroll taxes consist of the employer's and employee's shares combined. Lifetime Medicare spending includes Medicare spending for beneficiaries at or after age 65 (net of premiums that beneficiaries paid to the government). The dollar amounts are adjusted for inflation to 2016 dollars by using the gross domestic product deflator and discounted to age 65 by using the effective interest rate on all federal debt.

Figure 6.
Mean Present Value of Lifetime Medicare Taxes and Spending (Net of Premiums) as a Share of Lifetime Earnings by Quintile of Lifetime Household Earnings, Women



Amounts shown are ratios of lifetime Medicare taxes and spending to lifetime earnings for female beneficiaries age 65 or older born in the 1950s who live at least to age 65. Lifetime Medicare taxes include mostly payroll taxes paid to the program. Payroll taxes consist of the employer's and employee's shares combined. Lifetime Medicare spending includes total Medicare spending for beneficiaries at or after age 65 (net of premiums that beneficiaries paid to the government). Lifetime earnings are the present value of individual earnings over a lifetime.

Table 1.
Distribution of Individual Primary Insurance Amount Quintiles Conditional on Quintile of Lifetime Household Earnings

Quintile of Lifetime Household Earnings	Quintile of Individual PIA (Percent)						
	Missing	1	2	3	4	5	Count
				Men			
1	38	57	5	0	0	0	3,811
2	7	24	52	16	0	0	3,815
3	3	5	25	45	21	0	3,819
4	1	2	6	24	48	18	3,813
5	1	1	1	5	20	72	3,817
				Women			
1	47	36	15	2	0	0	4,100
2	15	25	30	24	7	0	4,101
3	8	13	22	29	24	5	4,099
4	4	6	12	20	33	24	4,099
5	3	4	6	10	21	56	4,105

Estimates are based on the cohorts born in the 1950s in the CBOLT sample who live at least to age 65.

Appendix A: Overview of the Congressional Budget Office's Long-Term Budget Model

After briefly describing the data source and structure of the Congressional Budget Office's long-term budget model (CBOLT), I focus on the models of differential mortality and individual earnings as well as the projections of total Medicare spending.[1] Those three components drive most of the variation in lifetime Medicare taxes and spending across beneficiaries of different socioeconomic status (SES) and different cohorts.

A.1. Structure of CBOLT

CBOLT is a microsimulation model of the U.S. population, economy, and federal budget.[2] CBOLT starts with a representative sample of the U.S. population. For each individual in that sample, CBOLT simulates annual demographic and economic transitions that follow the last sample year. The models of demographic transitions include fertility, death, immigration, emigration, marital transitions, and marital pairing; the models of economic transitions include labor force participation, hours worked, and earnings.

The individual-level data used in CBOLT come from the Continuous Work History Sample (CWHS), an administrative data set from the Social Security Administration. The data contain a history of individual earnings from 1951 to 2012 for a 1 percent sample of all Social Security numbers, and CBOLT uses a 10 percent random sample of CWHS. In CBOLT, earnings data up to 1983 are top-coded at the Social Security taxable maximum; starting in 1984, earnings

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[1]My analysis incorporates the long-term demographic, economic, and budgetary assumptions that underlie CBO's 2016 long-term budget projections (CBO 2016b).
[2]For more details on the model, see CBO (2009).

include wages and tips reported on Form W-2.[3] The data set also contains some basic demographic information and Social Security benefit status. Other demographic characteristics, such as education and marital status, are imputed.

Beyond 2012, an actuarial framework wraps around the microsimulation model to provide totals for demographic variables; a macroeconomic model provides totals for economic variables. The rates of individual demographic and economic transitions are set such that the total outcomes in each projection year match the totals provided by the actuarial and macroeconomic models. In addition, the actuarial framework further describes areas for which the microsimulation model has not yet been developed. (For example, CBOLT projects Medicare spending by using an actuarial framework.)

A.2. Model of Mortality

CBOLT's projections of mortality incorporate mortality improvement and differences in mortality rates across groups on the basis of historical patterns. CBO projects the average mortality rate for each five-year age group to fall at the same pace as the rate of decline between 1950 and 2012. The projections incorporate a slower decline in mortality rates for people in older age groups, consistent with the historical pattern. CBO projects that someone who turns 65 in 2040 can be expected to live another 21 years, on average, or about 2 years longer than someone turning 65 in 2015 is expected to live.

In addition, the projected rate of decline in mortality rate varies across individuals on the basis of the historical relationship between the one-year mortality rate and a set of individual characteristics, which include age, sex, cohort, education, marital status, and lifetime earnings.[4]

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[3]Olsen and Hudson (2009) give more information on data collection and limitations of Social Security earnings records.
[4]Cristia (2007) describes the model of differential mortality used in CBOLT.

CBO expects people who are married, have more education, and are in higher-income groups to live longer.

A.3. Model of Individual Earnings

Projections of individual earnings are more important for younger cohorts. For the 1950s cohort in my main analysis, I observe most of their earnings histories in CWHS.

The model of individual earnings includes both a model of labor force participation (including employment and hours worked) and a model of earnings conditional on labor force participation.[5] The projections of employment and hours worked are based on historical variation by age, sex, cohort, education, marital status, number of children under age 6, and Social Security benefit status. The models also account for persistence in employment and hours worked.

Earnings in CBOLT are the sum of predicted earnings conditional on a set of individual characteristics and individual-specific shocks correlated over time. The predicted earnings are based on the same set of individual characteristics as in the models of labor force participation. The individual-specific shocks consist of an annual permanent shock that accumulates and a one-time transitory shock.

The projected individual earnings are adjusted such that the total earnings and the distribution of earnings are consistent with the macroeconomic model in each projection year.[6] The historical pattern of rising earnings inequality is projected to continue for the next decade, but earnings inequality generally ceases to rise after the first decade.

A.4. Model of Total Medicare Spending and Premiums

[5]CBO (2006) describes the model of labor force participation in CBOLT. Schwabish and Topoleski (2013) describe the projections of individual earnings in CBOLT.
[6]See CBO (2016b, 98) for CBOLT's projection of earnings inequality as measured by the share of earnings below the taxable maximum.

The long-term projections of total Medicare spending combine projections of the number of Medicare beneficiaries with projections of spending per beneficiary.[7] The number of Medicare beneficiaries age 65 or older grows with population, and the number of beneficiaries under age 65 grows with the number of recipients of Social Security disability benefits. Medicare spending per beneficiary varies by age, sex, and number of years until death.[8] That average spending grows at the same rate for all groups in each projection year. CBO projects that growth rate by combining projected growth in potential gross domestic product per capita and projected excess cost growth for Medicare. CBO projects that the excess cost growth rate for Medicare will rise linearly from 0.9 to 1.0 between 2027 and 2046.

The projections of total Medicare premiums are based on the projections of total Medicare spending and income distribution of beneficiaries age 65 or older. The basic premiums for Part B and Part D are set to cover a certain percentage of total expenditures in those programs, so total premiums in those programs grow with total Medicare spending.[9] High-income beneficiaries pay additional premiums for Part B and Part D. Income-related premiums are calculated based on the income distribution of the beneficiaries age 65 or older and the amount of additional premiums as specified in law.

[7]Chapter 3 of CBO (2016b) further describes the long-term projections of federal health care spending.

[8]The variable of time until death has three categories: dying in the current year, dying in the next calendar year, and dying after the next calendar year. Sabelhaus, Simpson, and Topoleski (2004) discuss how the variation in average spending by time until death affects projections of total Medicare spending.

[9]For Part B, premiums paid by beneficiaries cover about one-quarter of expenditures. Enrollees' premiums under Part D are set to cover about one-quarter of the cost of the basic prescription drug benefit (although many low-income enrollees pay no premiums).

Appendix B: Primary Insurance Amount and Annual Medicare Spending

To estimate the relationship between primary insurance amount (PIA) and annual Medicare spending, I use the National Health Interview Survey (NHIS), which is linked to Medicare and Social Security administrative files. That approach captures the variation in both Medicare enrollment and spending across individuals.

B.1. Estimation Method

I estimate the relationship between PIA and annual spending on Part A and Part B in two steps.[1] I first estimate how the decision of Medicare enrollment varies with individual characteristics.[2] I then examine factors that affect the level of Medicare spending accounting for individual enrollment decisions.

First, I use a logit model to examine the choice of Medicare enrollment. Fewer beneficiaries are enrolled in Part B only than in Part A only.[3] To simplify my model of enrollment choice, I assume all the people age 65 or older are enrolled in Part A, and the dependent variable is an indicator variable that takes on the value of 1 if the beneficiary is

[1]The regression analysis does not include spending for the Medicare Advantage program and Part D. The data section describes the spending measures.

[2]Part A and Part B provide coverage for different types of services, and not every beneficiary enrolls in both parts. Medicare Part A covers mainly inpatient services that hospitals provide; Part B covers mainly outpatient services that physicians and hospitals' outpatient departments provide. Beneficiaries could delay enrollment in Part B without penalty if they have alternative sources of coverage.

[3]In my sample, less than 1 percent of beneficiaries are enrolled in Part B only, compared with 4 percent for those enrolled in Part A only and 95 percent for those enrolled in both Parts A and B. The share enrolled in both Parts A and B is lower among younger Medicare beneficiaries age 65 or older. In my sample, among those between ages 65 and 69, the share enrolled in both Parts A and B is 94 percent, compared with 98 percent for those ages 80 and above. The share enrolled in Part B only is relatively stable across age groups among beneficiaries age 65 or older; the share enrolled in Part A only is much greater at younger ages. The share of beneficiaries enrolled in Part A only has increased steadily over the past decade. How such a shift in enrollment patterns affects the distribution of Medicare is unclear. If people of higher SES prefer to work longer and delay enrollment in Part B, lifetime spending would rise more slowly and lifetime taxes would rise faster for those beneficiaries than for those with lower SES.

enrolled in Part B.[4] The model of enrollment also includes an indicator variable for Part B enrollment in the previous year to account for persistence in enrollment choice.

Second, I estimate a two-stage model of Medicare spending controlling for Medicare enrollment and PIA.[5] In the first stage, I use a logit model to estimate the likelihood of having positive spending. That logit model includes an indicator variable for positive spending in the previous year to account for persistence in spending. In the second stage, for beneficiaries with positive annual spending, I use a linear model to estimate how the log of annual spending varies with different brackets of PIA. To account for persistence in spending, I model the residuals by using a first-order autoregressive, or AR(1), linear model.

To account for changes in the composition of Medicare beneficiaries in my projections, the regression models include other individual characteristics besides PIA. Additional independent variables include an indicator variable for age 65, age, age squared, an indicator variable for Part B enrollment (to analyze Medicare spending), an indicator variable for marital status, an indicator variable for disability (as defined by eligibility for Disability Insurance), a set of indicator variables for number of years until death, a set of indicator variables for educational attainment, and a set of indicator variables for calendar years.[6] The model is estimated separately for four age groups. The projections based on the estimated relationship between those characteristics and spending incorporate the effects of projected changes in population

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[4]Average spending among beneficiaries enrolled in Part B only is lower than those enrolled in both Parts A and B, but it is much higher than those enrolled in Part A only. Average spending among fee-for-service (FFS) beneficiaries in my sample is less than $4,000 for beneficiaries enrolled in Part B only, compared with about $700 for those enrolled in Part A only, and greater than $6,000 for those enrolled in both Parts A and B.

[5]Buntin and Zaslavsky (2004) found that the two-part model with log transformation better predicts individual Medicare spending than more complicated generalized linear models.

[6]Time until death refers to a set of two indicator variables. The first indicator variable takes on the value of 1 if the person is dying in the current year; the second indicator variable takes on the value of 1 if the person is dying in the next calendar year; the omitted category includes people dying after the next calendar year.

demographics.[7] For example, including time until death in the model incorporates the likely negative effect of increases in life expectancy on annual spending. At any given age, average Medicare spending is significantly higher for beneficiaries closer to death. As life expectancy increases, given the relationship between time until death and annual spending, I would expect the share of beneficiaries close to death to decline at some ages, which would lead to a decline in average spending.

B.2. Sample Construction

The analysis uses NHIS survey data from 1994 to 2005 linked to administrative records from the Centers for Medicare & Medicaid Services (CMS) and the Social Security Administration. Using CMS administrative claims data allows me to construct a longitudinal sample of individual Medicare enrollment and spending; using Social Security administrative files allows me to construct my measure of permanent income. The survey questions from NHIS supply an additional set of individual characteristics.

NHIS is a cross-sectional annual household survey on health topics. Each survey includes about 100,000 individuals. Person weights are provided based on probabilities of selection into the survey.[8] The survey respondents are representative of the U.S. civilian noninstitutionalized population. (In the following discussion about the NHIS, *population* refers to the civilian noninstitutionalized population.)

I construct a longitudinal sample of Medicare enrollment and spending by using NHIS survey responses linked to administrative records from CMS and the Social Security Administration. I restrict my sample to beneficiaries born between 1905 and 1940. Even though

[7] My regression models do not control for health conditions. Therefore, my projected lifetime spending does not explicitly model potential changes in the health status of beneficiaries or their effects on spending.
[8] I account for the multistage sampling design of NHIS by using Stata's `svy` command for the estimation.

the NHIS is a cross-sectional survey, the linked CMS records provide Medicare enrollment and spending information for each linked survey respondent over multiple years.[9] To construct a longitudinal sample of enrollment and spending, for each survey respondent, I include all Medicare records between the year with the first available Medicare records (or the year in which he or she turned age 65 if that is from a later year) and the year 2005.[10] The panel of Medicare information for each survey respondent allows me to model the persistence in enrollment and spending and to increase the sample size, therefore making the estimates more precise. The linked Social Security administrative records provide a measure of permanent income, PIA, which supplements the demographic information from the NHIS.

I make two adjustments to the survey weights such that the set of survey respondents linked to Medicare records would be representative of Medicare beneficiaries age 65 or older from the year in which I obtain the Medicare information. The original survey weights incorporate the multistage sampling method and nonresponses, but they do not account for the nonrandom linkage between survey and administrative files or changes in the composition of beneficiaries between the year of survey and the year of the Medicare records.

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[9]Each NHIS respondent between 1994 and 1998 is linked to CMS records between 1991 and 2007, and each NHIS respondent between 1999 and 2005 is linked to CMS records between 1999 and 2007. About half of the survey respondents consented to linkage, so the linkage is not random and the likelihood of linkage varies with individual characteristics.

[10]My longitudinal sample might not be representative of the population of Medicare beneficiaries age 65 or older because the sampling frame of NHIS includes only the noninstitutionalized population. The institutionalized Medicare population consists mostly of residents in long-term care facilities. In 2006, about 6 percent of FFS Medicare beneficiaries lived in those facilities for at least a part of the year; and only a small share of those beneficiaries returned to the community within the first 6 months (Jacobson, Neuman, and Damico 2010). The survey sample does not include full-year residents of those facilities, so my estimates do not capture how Medicare spending varies with PIA for those beneficiaries. For respondents who are full-year residents of those facilities in a year other than the survey year, the linked sample contains their complete Medicare records in that year. For each part-year resident in the survey, the linked Medicare administrative data contain a complete record of Medicare spending during a year, including Medicare spending incurred during his or her nursing home stays. How including Medicare spending for full-year facility residents would affect my analysis is unclear. Existing evidence suggests that Medicare spending is higher for residents of long-term care facilities on average, and that difference is partly explained by the higher rate of mortality (Jacobson, Neuman, and Damico 2010). However, how the likelihood of residing in long-term care facilities or the costs of those residents to Medicare vary by PIA is unknown.

First, I account for the nonrandom linkage based on the variation in linkage eligibility by individual characteristics. The linkage to administrative records relies on personal identifying information, such as Social Security number or Medicare identification number. Only about half of the survey respondents provided personal information for linkage and were therefore eligible for data linkage. Among respondents eligible for linkage, almost all could be linked to the administrative records. Similar to the method in Judson, Parker, and Larsen (2013), I use a set of demographic characteristics to predict the likelihood of linkage eligibility to Medicare and Social Security records.[11] I then use the predicted likelihood of linkage eligibility to adjust the survey weights to generate a new set of person weights for the linked sample.[12] With the use of the adjusted weights, the set of survey respondents with a valid link to Medicare records from the year of the survey should represent Medicare beneficiaries in that year.

Second, I adjust the weights such that the set of survey respondents with a valid link to Medicare records from years other than the survey year would be representative of the Medicare beneficiaries in years in which I obtain Medicare records. After the two-step adjustment, the composition by age, sex, and race for respondents with linked Medicare information matches the composition of survey respondents in the year in which I obtain those Medicare records.[13]

B.3. Dependent Variables: Medicare Enrollment and Spending

[11]The outcome variable is the eligibility for linkage (that is, whether respondents supplied personal identifying information) rather than the presence of corresponding records in the administrative records. The reweighting process adjusts for the nonrandom decision to supply personal identifying information rather than the claiming behaviors of Social Security benefits.

[12]The reweighting is done separately for each survey year by using SUDAAN. The regression equation includes age, age squared, indicator variables for region (Northeast, North Central/Midwest, South, and West), education (missing, less than high school, high school graduate, some college, and bachelor's degree or above), and the interaction of race (missing, white, and nonwhite), ethnicity (Hispanic and non-Hispanic), and sex. Most of the coefficient estimates are statistically significant.

[13]I divide the sample into 16 demographic groups by age group (ages 65–69, 70–74, 75–79, and 80 or older), sex, and race (white and nonwhite). For each demographic group, I estimate the shares of respondents in the linked sample in both the survey year and the year in which I obtain their Medicare records. I use the person weights described in the previous paragraph to estimate those two shares. The ratio of those two shares is the multiplicative adjustment factor of person weights for that demographic group in the year other than the survey year.

Using information from CMS records, I construct measures of Medicare enrollment and spending. For enrollment, the records contain the number of months in a calendar year with enrollment in Medicare Part A or B. In a given year, a respondent is defined as a Part B enrollee for the year if he or she was enrolled in Part B for at least one month. The files also contain direct payments to providers for services covered by Medicare Part A and Part B: hospital inpatient services, post–acute care (including services provided by skilled nursing facilities and home health agencies), hospice care, hospital outpatient care, physician services, and durable medical equipment.[14] All spending measures are inflated to 2009 dollars by using the chained gross domestic product deflator. Only beneficiaries enrolled in fee-for-service (FFS) Medicare have all their spending on Medicare services processed and recorded by CMS, so the analysis of spending includes only beneficiaries with zero months of enrollment in a Medicare Advantage plan.[15]

B.4. Independent Variables: PIA and Other Individual Characteristics

To compute PIA and other demographic characteristics used in the regression analysis, I use survey responses, along with Social Security and Medicare administrative files.

I measure permanent income by using individual PIA value at age 65 (or the current Medicare eligibility age) from the Master Beneficiary Records (MBR) linked to the NHIS. If a person has applied for Social Security benefits by age 65, I obtain the PIA when he or she turns

[14]The administrative files do not include payments to Medicare Advantage plans, indirect payments to providers, or other program costs (such as administrative costs). Part D was implemented in 2006, so my data contain no information on Part D enrollment or spending.

[15]Most enrollees in Medicare are in the traditional FFS program, in which the federal government pays for covered services under Parts A and B directly. In 2016, about 30 percent have opted for the Medicare Advantage program, in which they receive Medicare benefits through a private health insurance plan. In my sample, less than 20 percent of Medicare beneficiaries are enrolled in Medicare Advantage plans.

65. If a person has not applied for Social Security benefits by age 65, I obtain the first available PIA and deflate it back to the year when he or she reaches age 65 by using the cost-of-living adjustment. My measure of PIA at age 65 would be consistent across beneficiaries if most beneficiaries applied for benefits by age 65 or shortly afterward. In a 1 percent sample of the MBR extracted on January 1, 2013, among people born between 1905 and 1940 who live at least to age 65, a little over 80 percent of those who ever applied for Social Security benefits applied at or before age 65 (Figure B1). For the cohorts in my sample, almost everyone applied for benefits by age 70 (Figure B2).[16]

To capture the possible nonlinear relationship between PIA and Medicare enrollment and spending, my regression models include a set of indicator variables for quintiles of PIA at age 65. The distribution of PIA values from the MBR linked to the NHIS could be different from the distribution for the same cohort who ever reached age 65 because some members of that cohort died before the survey year. Instead, I use a 1 percent random sample of the MBR extracted in January 2013 to estimate the quintile thresholds of the PIA distribution for each birth cohort. To get a sample consistent with my sample of beneficiaries age 65 or older in the NHIS, I include PIA information for those who survived until age 65. I estimate the quintile thresholds separately by sex and single year of birth.[17] Medicare beneficiaries with missing PIA are included in the analysis as a separate category. (To be consistent with the regression analysis, I assign PIA quintile by sex and birth year in CBOLT as well.)

[16]The MBR includes everyone on whose records a benefit application was ever filed, so it does not include information on PIA for survey respondents who will apply after the extraction date. Because the MBR linked to the survey is extracted in January 2009, by definition, only people who have ever applied before that date could have PIA on their records. For the youngest cohort in my sample, people born in 1940, that would be age 69. On the basis of the observed values in MBR extracted in 2013, most of that cohort applied for benefits before age 70, so my linked sample should include information on PIA for most survey respondents who would ever have one.

[17]To protect data confidentiality, each quintile threshold from the 1 percent MBR sample is the average of the threshold of 1 percentile above that quintile and the threshold of 1 percentile below that quintile.

In addition to the quintiles of PIA, I define additional demographic variables by using information from survey responses and administrative records. Age and sex are available in the NHIS, Medicare records, and the MBR. As much as possible, I use information from administrative records. I first assign age and sex by using the information from the MBR, followed by Medicare records and survey responses if the survey respondent is not linked to the MBR. For the year of death, I first assign the value on the basis of the information from the MBR, followed by Medicare records. From Medicare records, I obtain the original reason for entitlement code of Medicare, which indicates whether the respondent has any disability as defined by the Disability Insurance (DI) program at the first spell of Medicare enrollment.[18] Other explanatory variables from the survey responses include a set of indicator variables for educational attainment and an indicator variable for having ever been married.[19]

The analysis of survey respondents linked to Medicare records in years other than the survey is valid only if the characteristics used in the analysis do not change. PIA, sex, and race are fixed for each person. Education is unlikely to change because my sample includes only Medicare beneficiaries age 65 or older. Marital status could change, but for people age 65 or older the rate of change is likely to be very small.[20]

B.5. Summary Statistics

The linked sample of Medicare beneficiaries age 65 or older includes more than 750,000 observations. The number of observations varies over the sample period because of changes in

[18]Even though DI benefits are designed to assist people with conditions from which they are not expected to recover, a DI beneficiary might eventually recover. The disability variable indicates whether the person has ever received DI benefits.

[19]I define four categories of educational attainment (less than high school, high school graduate, some college, and bachelor’s degree or above) and two categories of marital status (never married and ever married—including currently married, divorced, and widowed).

[20]Because the variable of marital status is defined as “ever married,” the assignment of marital status would be wrong only if a person age 65 or older starts his or her first marriage spell during the sample period. The likelihood of starting one’s first marriage after age 65 is low.

the sampling method and in the linkage rate to Medicare records. Consistent with the composition of the U.S. population (Howden and Meyer 2011), the sample includes more women age 65 or older than men age 65 or older, especially at older ages (Table B1).

For the cohorts in my sample, men differ significantly from women along several dimensions (Table B2). For one, men have higher mortality rates, reflected in the larger share of older beneficiaries among women and a smaller share of women dying each year. Men in those birth cohorts also are more educated.

The most important difference between men and women is labor force participation, both in the degree of attachment and in the outcomes. More than a third of women do not have a PIA value, compared with 4.2 percent of men, most likely because of lacking enough work history to qualify for Social Security benefits on their own records.[21] Men age 65 or older also are more likely to have worked during the last week (data not shown). My definition of disability is based on the receipt of DI benefits, which depends on having enough work history. I observe a higher rate of disability among men, 9.6 percent versus 6.2 percent, even though men and women report similar health status in the sample (data not shown).[22]

Differences in labor force participation and earnings by sex lead to differences in the distribution of PIA values at age 65 (Figure B3). Both price inflation and earnings growth lead to higher PIAs for more recent cohorts. Within each cohort, the quintile thresholds are much higher for men because of their higher rate of labor force participation and higher average earnings.

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[21]In my NHIS sample, the share of women with missing PIA was lower for younger cohorts, declining from about 40 percent for the 1905 cohort to about 25 percent for the 1940 cohort. The share of men with missing PIA varied across cohorts, but it was generally below 10 percent. That result is consistent with women's increasing labor force participation for those cohorts.

[22]The estimates of work status during the last week and health status are based on a sample of respondents with linkage to Medicare records from the year of the survey only.

Men and women in my sample also differ in their distributions by PIA quintile because of differences in life expectancy. PIA quintile is assigned on the basis of all individuals who survived until age 65. Without differences in life expectancy at age 65, I would expect a uniform distribution of beneficiaries across five quintiles. Instead, in my sample, the share of men in the highest quintile (22 percent) is higher than the share in the lowest quintile (16 percent) (Table B2). That difference indicates a positive association between PIA quintile and life expectancy for men in my sample.[23] The women in my sample are more evenly distributed across PIA quintiles.

During my sample period, about 83 percent of beneficiaries age 65 or older are enrolled in traditional FFS Medicare only. The composition of beneficiaries between the full sample and the FFS sample is very similar (data not shown).

Among FFS beneficiaries, men differ from women in their Medicare enrollment and spending (Table B2). In both the full sample and the FFS sample, the rate of Part B enrollment is about 3 percentage points higher for women. Even though women have slightly higher rates of Part B coverage and higher rates of utilization (90 percent for women vs. 84 percent for men), they tend to have lower spending on average ($6,169 vs. $6,376). Higher spending on inpatient hospital services accounts for men's higher spending, which women's higher spending on post–acute care partially offsets.

B.6. Regression Results

Conditional on other individual characteristics, I generally find a statistically significant relationship between PIA and Medicare enrollment and spending. The coefficient estimates on other individual characteristics have the expected signs.

B.6.1. Coefficient Estimates on Quintiles of PIA

[23] That difference might also indicate that the linked NHIS sample is not representative of the population of covered workers in the Social Security administrative data, which are used to estimate the quintile thresholds of PIA.

The relationship between PIA and the likelihood of Part B enrollment differs for men and women (Table B3A).[24] At age 65, men in the fourth quintile are significantly more likely to be enrolled in Part B than those in other quintiles (column 1). For men older than 65, conditional on Part B enrollment in the previous year, the likelihood of Part B enrollment generally increases with PIA for men (columns 2–5). For women at age 65, the likelihood of enrollment in Part B tends to decline with PIA (column 6). For women older than age 65, the relationship between PIA and Part B enrollment does not follow the same pattern across age groups, though the likelihood of Part B enrollment tends to be the greatest for women in the highest PIA quintile (columns 7–10).[25] The magnitude of variation in the likelihood of Part B enrollment with respect to PIA quintile is much greater for men than for women. For all age groups, enrollment in Part B is highly persistent, as indicated by the large and statistically significant coefficient estimates on the lagged Part B enrollment.

The relationship between PIA and the likelihood of positive spending conditional on having positive spending in the previous year is generally positive for men; that relationship is not linear and only marginally significant for women (Table B3B). For men at age 65, the likelihood of positive spending is lowest for men in the second PIA quintile, and it starts to increase with PIA for those in higher PIA quintiles (column 1). The rate of increase is high: The likelihood of positive spending is about the same for those in the lowest PIA quintile and those in

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[24] I estimate the likelihood of enrollment in Part B and the likelihood of positive spending for beneficiaries at age 65 without controlling for the lagged status because most of those beneficiaries were new to Medicare.

[25] Because the regression models control for enrollment status in the previous year and older beneficiaries are more likely to enroll in Part B, the coefficient estimates on PIA quintiles conditional on the lagged enrollment have higher standard errors for beneficiaries at older ages. Because my model of Part B enrollment controls for enrollment status during the last year, the positive coefficients on PIA quintiles indicate a greater likelihood of new Part B enrollees for those with higher PIA. Those results are consistent with the hypothesis that beneficiaries with higher PIA tend to work longer and enroll in Part B later. In my NHIS sample, that lower rate of Part B enrollment for Medicare beneficiaries who worked during the last week is evident. Among those who did not work during the last week, almost everyone was enrolled in Part B; about 85 percent of those who reported working during the last week were enrolled in Part B.

the third PIA quintile. For men between 66 and 69, I observe a similar nonlinear relationship between PIA and the likelihood of positive spending as beneficiaries at age 65; for those age 70 and above, that relationship is generally positive (columns 3–5). For women at age 65, the likelihood of positive spending does not vary significantly with PIA (column 6). For women above age 65, the relationship varies across age groups. The likelihood of positive spending tends to be higher for people in the lowest and highest PIA quintiles, but the differences across quintiles are only marginally significant (columns 7–10). The likelihood of positive spending is highly persistent.

Conditional on receiving some Medicare services in a year, spending tends to be highest for beneficiaries in the lowest PIA quintile, and the magnitude of the variation in spending across PIA quintiles is greater for younger beneficiaries (Table B3C). For men ages 65–69, after an initial decline between the lowest and second quintiles, log of spending increases with PIA quintile such that the difference between the second and highest quintiles is statistically significant (column 1). Spending for men in the second PIA quintile is about 27 percent lower than that for those in the lowest PIA quintile. For men age 70 or older, spending is lowest for those in the second PIA quintile and not statistically different for other PIA quintiles (columns 2–4). For women between 65 and 69, spending stays roughly constant with respect to PIA after an initial decline between the lowest and the third PIA quintiles. Spending for women in the third PIA quintile is about 15 percent lower than that for those in the lowest PIA quintile. The variation in spending with respect to PIA is similar for women ages 70–74 and 65–69 (columns 5 and 6). For women 75 or older, spending does not vary significantly with PIA (columns 7 and 8).

I estimate the persistence of spending level by using the regression residuals and an AR(1) model. The coefficients on the lagged residual are positive and highly significant for all groups (Table B3C). The positive coefficients on lagged residuals and on lagged indicator variables for positive spending suggest that any shock to the predicted level of spending in a given year would persist. That persistence implies a greater dispersion in lifetime spending across individuals than would occur in a model in which the shocks are independent over time. As noted, because my analysis focuses on comparing average lifetime spending across several groups, rather than variation across individuals, accounting for the persistence in spending has a small quantitative effect on my results.

Household structure might explain some of the difference between men and women in the patterns of Medicare enrollment and spending with respect to PIA quintiles. Results in the literature have emphasized the importance of household resources for decisions about consumption. Earnings of a spouse would be important for a person's decision on insurance purchase and health care spending. Because men tend to contribute a greater share to household resources for the cohorts in my sample, I would expect a stronger relationship between individual PIA and Medicare enrollment (and spending) for men. As expected, my regression estimates show that the magnitude of variation in coefficients across PIA quintiles is greater for men.

The nonlinear relationship between PIA and annual spending could reflect the availability of Medicaid coverage for low-income Medicare beneficiaries or for dual-eligible beneficiaries of Medicare and Medicaid. Medicaid coverage for those dual beneficiaries pays for Medicare premiums, and it pays for cost sharing of Medicare-covered services for some of those dual-eligible beneficiaries. Health insurance coverage with lower cost sharing tends to increase demand for health care services.

B.6.2. Coefficient Estimates on Other Individual Characteristics

The association between individual characteristics and Part B enrollment is stronger at younger ages and is similar for men and women (Table B3A). Except for age 65, the models include the status of Part B enrollment in the previous year. The regression coefficients for the model at age 65 reflect the effects on the likelihood of Part B enrollment, and the coefficients from the other models reflect the effects on the likelihood of taking up Part B in the current year. Enrollment in Part B is strongly persistent. At age 65, beneficiaries who have ever been married and those who are more educated are less likely to have Part B coverage; the disabled and those with higher mortality risk are more likely to have Part B coverage (columns 1 and 6). Those results are consistent with my expectations. People who continue working (for example, more educated workers) and have additional sources of health insurance (for example, married people) might delay Part B enrollment; those who have greater needs for medical services (for example, the disabled and those with higher mortality risk) are more likely to have Part B coverage. For older beneficiaries, I focus my discussion on those between ages 66 and 69 because most of the older beneficiaries have Part B coverage and very few are new Part B enrollees (columns 2 and 7). The rate of new Part B enrollees declines with age at a decreasing rate probably because with age, the share of beneficiaries with Part B coverage increases and the number of new enrollees decreases. As with the results at age 65, being more educated is associated with a lower rate of new Part B enrollment; greater mortality risk is associated with a higher rate of new Part B enrollment. Disability status and having ever been married have no statistically significant effect on enrollment.

Medicare spending is highly persistent, and it varies significantly with the set of individual characteristics in my models for both men and women. I discuss both the likelihood of positive spending and the spending level conditional on having positive spending.

The likelihood of positive spending varies significantly with individual characteristics (Table B3B). The models for beneficiaries age 66 or older include the status of having positive spending in the previous year. At age 65, having Part B coverage, disability, greater mortality risk, and greater education attainment are associated with greater likelihood of positive Medicare spending; marital status does not have a statistically significant effect on the likelihood of having positive spending (columns 1 and 6). For older beneficiaries, conditional on having positive spending in the previous year, having ever been married, greater mortality risk, and greater education attainment are associated with greater likelihood of having positive spending at all ages. Disability also is associated with a greater likelihood of positive spending, and that association is much stronger for women (columns 2–5 and 7–10). Those results are consistent with my expectations that a greater demand for medical services is associated with a greater likelihood of positive Medicare spending. For both women and women ages 66–69, the likelihood of positive spending declines with age at a decreasing rate; age has no statistically significant effect on the likelihood of positive spending at older ages. The share of beneficiaries with positive spending increases with age. Conditional on the spending outcome in the previous year and other measures of needs for medical services, one can reasonably conclude that age does not independently affect the likelihood of positive spending.

Among beneficiaries with positive spending, the level of spending varies significantly with individual characteristics (Table B3C). Beneficiaries cost less at age 65 because most of them are eligible for Medicare for only part of the calendar year (columns 1 and 5). Age does not independently affect the spending level except for the very old (people age 80 or older). For the very old, log of spending increases with age at a decreasing rate (columns 4 and 8). As expected, having ever been married, disability, and higher mortality risk are associated with a higher spending level at all ages (columns 1–8). The association between education and spending level is strong for women. Conditional on having positive Medicare spending, the spending level tends to be lower for more educated women ages 65–74. For older beneficiaries, spending is lowest for high school graduates and similar for beneficiaries in other education categories (that is, less than high school, some college, and college graduates). Although Part B enrollment is associated with a greater likelihood of positive spending, conditional on having positive spending and other measures of demand for medical services, Part B enrollment is associated with a lower spending level at all ages. Part B enrollees might use medical services more often because of the more comprehensive insurance coverage, but they might need less costly services because of better access to preventive care.

B.6.3. Spending by Service Type

For most subgroups, the relationship between PIA quintiles and Medicare spending is not monotonic. Those patterns could be the result of heterogeneity in the demand for different types of Medicare services across socioeconomic status groups, for reasons such as financial constraints or health status. To better understand the estimated nonmonotonic relationship between socioeconomic status and spending and to evaluate the plausibility of my results, I examine how the relationship between PIA and Medicare spending varies across Medicare-covered services.

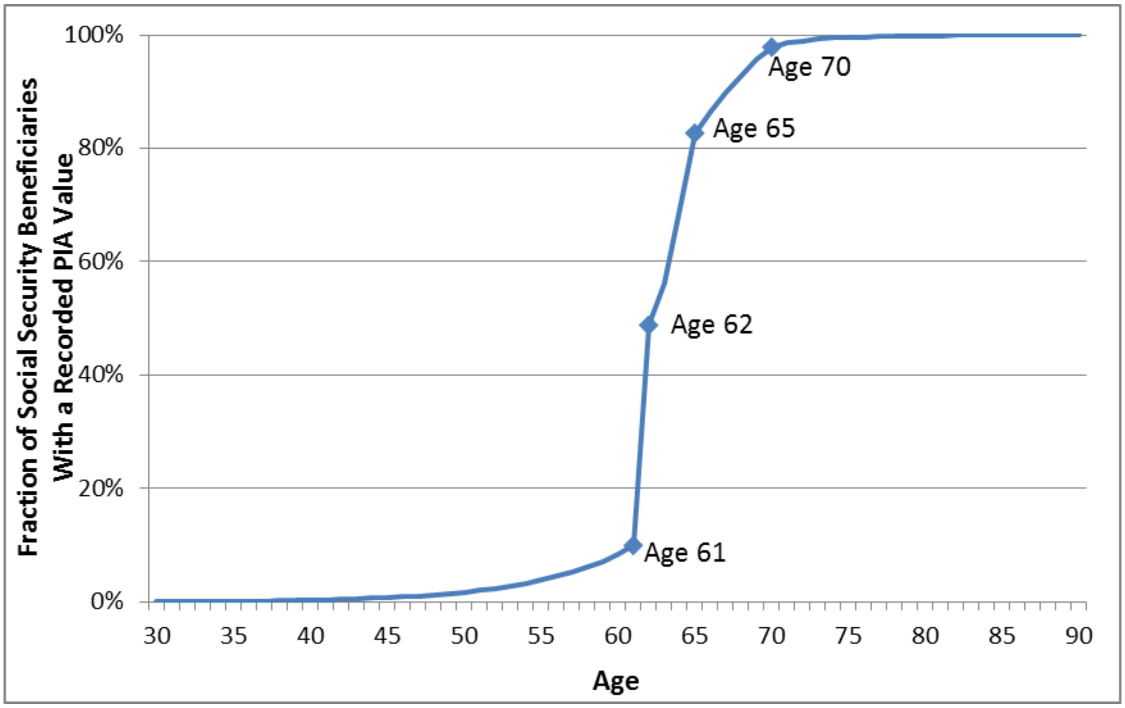
Both men and women with higher PIA are less likely to use inpatient hospital care and post–acute care, but the patterns of use for outpatient hospital care and physician services differ for men and women (Table B4A). The likelihood of having positive spending in inpatient hospital care and post–acute care is lower for those with higher PIA. The relationship between PIA and the likelihood of having positive spending on outpatient hospital care is a U-shaped curve for men and negative for women. For men, that likelihood initially declines with PIA before it starts to rise with PIA again. Beneficiaries in the second PIA quintile have the lowest likelihood and those in the lowest and third PIA quintiles have similar likelihoods. For women, that likelihood declines between the lowest and second PIA quintiles and stays relatively constant between the second and fourth PIA quintiles. The relationship between PIA and the likelihood of having positive spending in physician services has a U-shaped curve for men and women, but the pattern and magnitude of the variation are different. For men, the likelihood of having positive spending in physician services declines between the lowest and second PIA quintiles, and it increases with PIA after the second PIA quintile such that the likelihood is much higher for beneficiaries in the highest PIA quintile than those in the lowest PIA quintile. For women, that likelihood is similar for those in the lowest and highest PIA quintiles, and it is the lowest for those in the middle PIA quintile. The likelihood of having positive spending in durable medical equipment generally declines with PIA.

Among beneficiaries with positive spending in a type of services, the variation of spending level with respect to PIA differs for men and women (Table B4B). For women, average spending on inpatient hospital care and post–acute care does not vary significantly with PIA. For men, average spending on inpatient hospital care is about the same for beneficiaries with different PIA levels except for men in the second PIA quintile, whose average spending is about 8 percent lower. Average spending on post–acute care is generally lower for male beneficiaries with higher PIA. The spending on hospital outpatient care is generally lower for those with higher PIA. The relationship between PIA and physician services has a U-shaped curve for both men and women. For women, spending on physician services for beneficiaries between the second and fourth PIA quintiles is about 4 percent to 5 percent lower than those in the lowest

PIA quintile. For men, average spending on physician services declines about 13 percent between the lowest and second PIA quintiles, and it starts to increase with PIA such that average spending for those in the highest PIA quintile is about 10 percent higher than those in the lowest PIA quintile.

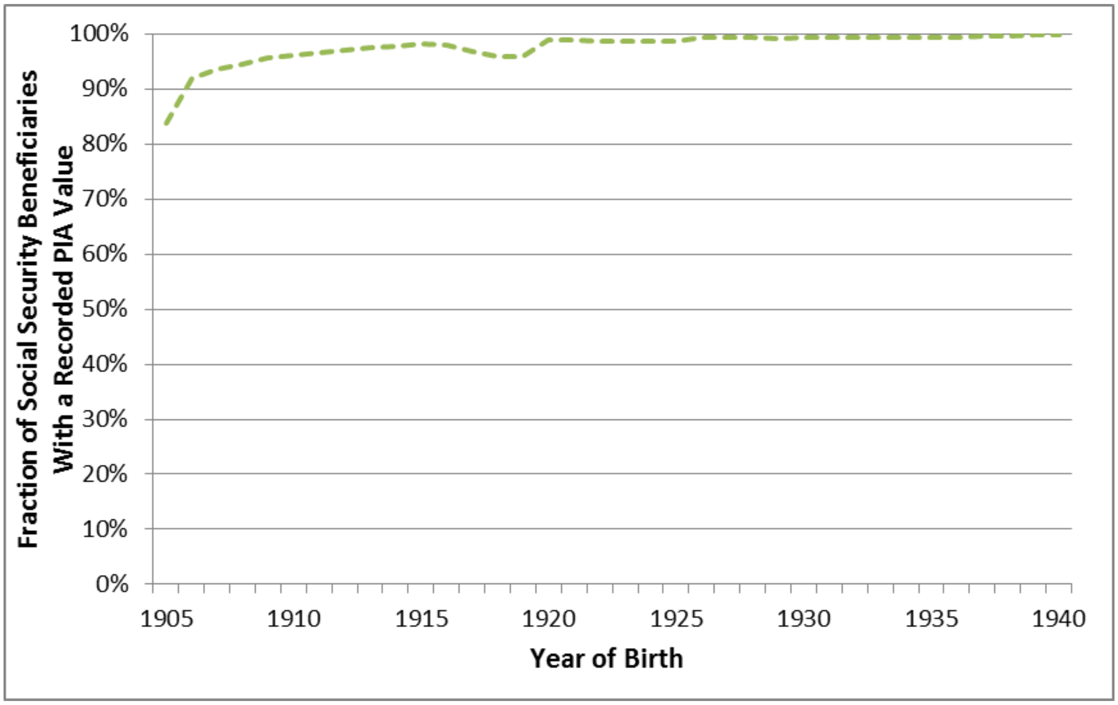
The regression results by service type suggest that the nonlinear relationship between PIA and annual Medicare spending is partly driven by the differences in the types of services received by beneficiaries of different SES. People of lower SES tend to use more intensive care such as hospital inpatient services and post–acute care; people of higher SES might receive more preventive care or have better access to care management as suggested by their greater use of hospital outpatient services and physician services.

Figure B1.
Fraction of Social Security Beneficiaries With a Recorded Primary Insurance Amount (PIA) Value, by Age



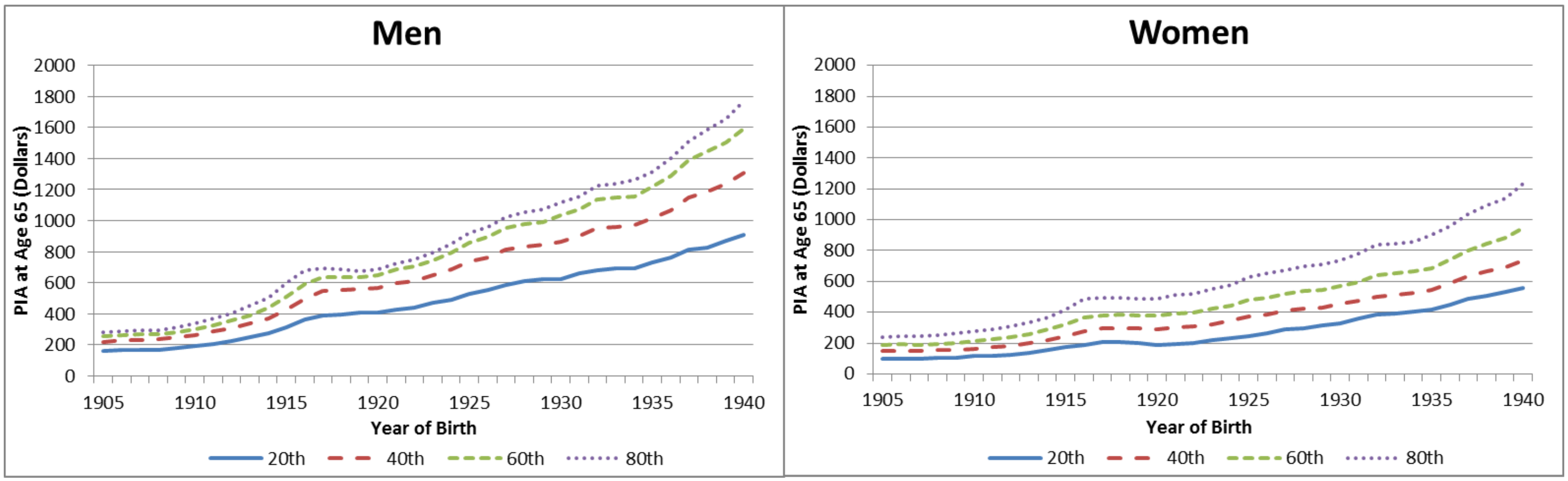
Estimates are based on the 1 percent sample of the Master Beneficiary Records extracted in January 2013. The sample includes cohorts born between 1905 and 1940 who live at least to age 65.

Figure B2.
Fraction of Social Security Beneficiaries With a Recorded Primary Insurance Amount (PIA) Value by Age 70



Estimates are based on the 1 percent sample of the Master Beneficiary Records extracted in January 2013. The sample includes cohorts born between 1905 and 1940 who live at least to age 65.

Figure B3.
Thresholds for Primary Insurance Amount (PIA) Quintiles by Sex and Birth Year



Estimates are based on the 1 percent sample of the Master Beneficiary Records extracted in January 2013. The sample includes cohorts born between 1905 and 1940 who live at least to age 65. To protect data confidentiality, the threshold for each quintile is the average of the thresholds for one percentile and one percentile below that quintile.

Table B1.
Sample Size by Sex and Age Group

	Men				Women				
Year	**65–69**	**70–74**	**75–79**	**80+**	**65–69**	**70–74**	**75–79**	**80+**	**Total**
1994	5,147	4,432	2,933	2,224	6,302	5,670	4,137	4,048	34,893
1995	5,270	4,632	3,276	2,656	6,332	5,891	4,415	4,738	37,210
1996	5,266	4,738	3,576	3,045	6,299	5,956	4,709	5,373	38,962
1997	5,290	4,779	3,699	3,427	6,262	6,070	4,938	5,943	40,408
1998	5,226	4,829	3,813	3,743	6,088	6,171	5,119	6,484	41,473
1999	9,924	8,887	6,882	6,339	11,169	10,988	9,270	10,683	74,142
2000	10,063	9,092	7,116	7,004	11,311	11,041	9,584	11,663	76,874
2001	10,223	9,164	7,276	7,668	11,447	11,009	9,752	12,640	79,179
2002	10,427	9,251	7,456	8,251	11,475	10,980	9,934	13,495	81,269
2003	10,702	9,209	7,573	8,729	11,701	10,834	10,006	14,309	83,063
2004	10,857	9,290	7,653	9,130	11,860	10,760	9,942	15,106	84,598
2005	11,103	9,173	7,749	9,544	12,127	10,764	9,910	15,705	86,075

Estimates are based on the linked National Health Interview Survey sample, 1994–2005. The sample includes survey respondents age 65 or older linked to Medicare administrative files between 1994 (or the year they turn 65) and 2005. The year corresponds to the year of the Medicare administrative files.

Table B2.
Summary Statistics

Variable	Men Mean	Men SE	Women Mean	Women SE
FFS Enrollment	83.0%	0.3%	82.9%	0.3%
Age	73.8	0.04	74.8	0.04
65–69	32.2%	0.2%	28.2%	0.2%
70–74	26.8%	0.1%	25.3%	0.1%
75–79	20.9%	0.1%	21.7%	0.1%
80+	20.0%	0.2%	24.9%	0.2%
Married	96.2%	0.1%	96.4%	0.1%
Disabled	9.6%	0.2%	6.2%	0.1%
Time Until Death				
Death this year	3.4%	0.0%	2.5%	0.0%
Death next year	3.9%	0.0%	3.0%	0.0%
Death after next year	92.6%	0.1%	94.5%	0.1%
Education				
Less than high school	30.6%	0.3%	31.5%	0.3%
High school graduate	30.7%	0.3%	39.3%	0.3%
Some college	16.8%	0.2%	17.4%	0.2%
Bachelor's degree or above	21.9%	0.3%	11.9%	0.2%
Quintile of Primary Insurance Amount				
1	16.4%	0.2%	12.9%	0.2%
2	17.9%	0.2%	13.1%	0.2%
3	19.3%	0.2%	13.4%	0.2%
4	20.2%	0.2%	12.8%	0.2%
5	22.0%	0.3%	13.1%	0.2%
Missing	4.2%	0.1%	34.7%	0.3%
Part B coverage	94.9%	0.1%	97.4%	0.1%
	Fee-for-Service Sample			
Fraction With Positive Spending				
Total	83.7%	0.2%	90.4%	0.1%
Inpatient hospital	18.6%	0.1%	18.9%	0.1%
Post–acute care	7.9%	0.1%	10.5%	0.1%
Hospice	1.1%	0.0%	1.0%	0.0%
Outpatient hospital	56.9%	0.3%	67.1%	0.2%
Physician	81.9%	0.2%	89.2%	0.1%
Durable medical equipment	18.7%	0.2%	22.4%	0.2%
Average Medicare Spending (2009 Dollars)				
Total	6,376	48.8	6,169	43.6
Inpatient hospital	3,047	28.9	2,668	24.3
Post–acute care	565	9.8	816	12.0
Hospice	83	4.5	91	3.6
Outpatient hospital	659	10.0	639	8.3
Physician	1,825	15.1	1,761	11.6
Durable medical equipment	197	3.8	194	3.4

Estimates are based on the linked National Health Interview Survey sample, 1994–2005. The sample includes survey respondents age 65 or older linked to Medicare administrative files between 1994 (or the year they turn 65) and 2005. All spending measures are inflated to 2009 dollars by using the chained gross domestic product deflator.

Table B3.
Estimated Regression Coefficients

(A) Likelihood of Enrollment in Part B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Men					Women				
	65	66–69	70–74	75–79	80+	65	66–69	70–74	75–79	80+
Lagged Part B Enrollment		7.054***	8.796***	10.406***	10.728***		7.491***	9.286***	10.664***	12.750***
		(0.089)	(0.153)	(0.286)	(0.345)		(0.120)	(0.190)	(0.281)	(0.439)
Age		–11.106***	–4.004	–2.488	0.356		–16.471***	–4.466	4.891	0.846
		(3.856)	(4.059)	(7.714)	(1.197)		(4.611)	(4.653)	(12.500)	(1.300)
Age Squared (/100)		8.142***	2.703	1.627	–0.229		12.094***	3.092	–3.300	–0.562
		(2.858)	(2.822)	(5.021)	(0.685)		(3.419)	(3.235)	(8.163)	(0.754)
Ever Married	–0.356***	–0.288*	–0.308	–0.795**	1.041*	–0.020	–0.215	–0.716**	0.203	1.972***
	(0.136)	(0.173)	(0.244)	(0.330)	(0.536)	(0.135)	(0.202)	(0.331)	(0.612)	(0.674)
Disabled	1.537***	–0.200*	–0.345*	–0.300	–0.424	2.041***	0.293	0.367	0.508	0.515
	(0.112)	(0.116)	(0.184)	(0.303)	(0.527)	(0.191)	(0.192)	(0.314)	(0.617)	(1.259)
Death This Year	0.235	–0.226	0.284	–0.036	0.171	0.047	–0.071	–0.204	–0.916	–0.447
	(0.275)	(0.214)	(0.293)	(0.377)	(0.327)	(0.442)	(0.529)	(0.369)	(1.248)	(0.987)
Death Next Year	0.825***	0.339*	0.467*	1.109***	0.544	1.674***	0.597*	0.467	–0.769***	–1.090
	(0.221)	(0.201)	(0.254)	(0.324)	(0.597)	(0.528)	(0.308)	(0.432)	(0.290)	(0.769)
Death After Next Year						*Omitted*				
Less Than High School						*Omitted*				
High School Graduate	–0.275***	–0.133	0.068	0.451**	–0.549	–0.164**	–0.133	–0.125	0.292	–0.281
	(0.068)	(0.089)	(0.129)	(0.217)	(0.363)	(0.078)	(0.095)	(0.158)	(0.354)	(0.429)
Some College	–0.270***	–0.277***	–0.231	0.103	0.277	–0.413***	–0.135	–0.065	0.367	–1.131***
	(0.074)	(0.097)	(0.149)	(0.242)	(0.435)	(0.086)	(0.109)	(0.169)	(0.317)	(0.420)
Bachelor's Degree or Above	–0.501***	–0.156*	–0.069	–0.279	0.280	–0.586***	–0.252**	0.062	0.483	–0.698
	(0.074)	(0.093)	(0.138)	(0.236)	(0.355)	(0.089)	(0.126)	(0.187)	(0.381)	(0.530)
1st PIA Quintile						*Omitted*				
2nd PIA Quintile	–0.039	0.090	0.226	0.043	0.127	–0.134	–0.071	0.491**	–0.502	1.265**
	(0.078)	(0.107)	(0.151)	(0.244)	(0.463)	(0.099)	(0.139)	(0.236)	(0.659)	(0.565)
3rd PIA Quintile	–0.014	0.267***	0.511***	0.478*	0.822*	–0.388***	0.168	0.170	0.491	0.202
	(0.073)	(0.099)	(0.154)	(0.272)	(0.420)	(0.097)	(0.124)	(0.223)	(0.381)	(0.473)
4th PIA Quintile	0.316***	0.492***	0.682***	0.617**	0.383	–0.624***	0.159	0.390*	0.564	0.677
	(0.080)	(0.101)	(0.165)	(0.284)	(0.582)	(0.097)	(0.129)	(0.215)	(0.353)	(0.481)
5th PIA Quintile	–0.002	0.422***	0.868***	1.201***	0.860**	–0.500***	0.390***	0.411*	0.979***	1.139***
	(0.081)	(0.098)	(0.147)	(0.262)	(0.348)	(0.090)	(0.132)	(0.225)	(0.346)	(0.427)
Missing PIA	0.805***	0.175	–0.072	0.128	–0.066	0.351***	0.414***	0.179	0.369	0.339
	(0.191)	(0.207)	(0.233)	(0.418)	(0.361)	(0.092)	(0.123)	(0.208)	(0.297)	(0.390)
Constant	2.434***	377.530***	146.256	92.701	–17.773	2.614***	559.655***	160.323	–183.839	–36.093
	(0.175)	(130.041)	(145.851)	(296.226)	(52.357)	(0.181)	(155.412)	(167.211)	(478.502)	(56.028)
Observations	20,567	70,376	78,843	63,064	67,150	22,655	79,711	95,363	83,480	112,336

(B) Likelihood of Positive Spending

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Men					Women				
	65	66–69	70–74	75–79	80+	65	66–69	70–74	75–79	80+
Lagged Positive Spending		2.718***	3.194***	3.271***	3.363***		3.088***	3.369***	3.567***	3.610***
		(0.037)	(0.042)	(0.054)	(0.063)		(0.045)	(0.048)	(0.060)	(0.060)
Part B Enrollment	4.949***	3.829***	3.268***	2.827***	2.484***	5.277***	4.217***	3.811***	3.247***	2.955***
	(0.171)	(0.084)	(0.086)	(0.099)	(0.138)	(0.194)	(0.108)	(0.118)	(0.173)	(0.136)
Age		–15.323***	0.295	1.891	0.591*		–21.777***	–2.526	–1.440	0.289
		(2.119)	(1.460)	(1.866)	(0.310)		(2.222)	(1.566)	(2.141)	(0.218)
Age Squared (/100)		11.292***	–0.177	–1.209	–0.334*		16.032***	1.807*	0.956	–0.162
		(1.571)	(1.015)	(1.213)	(0.182)		(1.647)	(1.088)	(1.391)	(0.127)
Ever Married	0.131	0.372***	0.493***	0.345***	0.542***	0.190*	0.402***	0.477***	0.548***	0.424***
	(0.090)	(0.074)	(0.078)	(0.094)	(0.093)	(0.111)	(0.090)	(0.104)	(0.120)	(0.131)
Disabled	1.311***	0.183***	0.008	–0.017	–0.010	1.792***	0.419***	0.456***	0.403**	0.180
	(0.069)	(0.049)	(0.061)	(0.083)	(0.104)	(0.100)	(0.094)	(0.109)	(0.161)	(0.169)
Death This Year	1.284***	1.220***	1.060***	0.646***	0.460***	1.076**	1.255***	1.344***	0.701***	0.366***
	(0.311)	(0.175)	(0.159)	(0.160)	(0.112)	(0.422)	(0.305)	(0.285)	(0.245)	(0.112)
Death Next Year	0.497***	0.318**	0.629***	0.488***	0.576***	0.817***	0.476**	0.280*	0.590***	0.411***
	(0.167)	(0.123)	(0.107)	(0.125)	(0.090)	(0.256)	(0.185)	(0.152)	(0.163)	(0.103)
Death After Next Year						*Omitted*				
Less Than High School						*Omitted*				
High School Graduate	0.027	0.101**	0.276***	0.211***	0.054	0.071	0.172***	0.205***	0.063	0.066
	(0.054)	(0.043)	(0.045)	(0.055)	(0.069)	(0.051)	(0.052)	(0.050)	(0.060)	(0.058)
Some College	0.051	0.146***	0.301***	0.245***	0.225***	0.127**	0.230***	0.240***	0.206***	0.207**
	(0.064)	(0.049)	(0.057)	(0.071)	(0.084)	(0.058)	(0.062)	(0.061)	(0.078)	(0.083)
Bachelor's Degree or Above	0.228***	0.313***	0.504***	0.327***	0.289***	0.164**	0.252***	0.449***	0.172*	0.344***
	(0.064)	(0.050)	(0.054)	(0.073)	(0.082)	(0.064)	(0.067)	(0.080)	(0.096)	(0.100)
1st PIA Quintile						*Omitted*				
2nd PIA Quintile	–0.266***	–0.226***	–0.091*	–0.048	–0.045	–0.033	–0.022	–0.148*	–0.058	–0.220**
	(0.064)	(0.049)	(0.055)	(0.071)	(0.087)	(0.071)	(0.075)	(0.084)	(0.104)	(0.109)
3rd PIA Quintile	0.016	0.079	0.056	0.107	0.263***	–0.081	–0.104	–0.047	–0.045	–0.236**
	(0.062)	(0.051)	(0.056)	(0.074)	(0.091)	(0.070)	(0.068)	(0.085)	(0.104)	(0.113)
4th PIA Quintile	0.297***	0.282***	0.365***	0.326***	0.337***	–0.031	–0.007	–0.176**	0.138	–0.162
	(0.062)	(0.055)	(0.057)	(0.078)	(0.096)	(0.075)	(0.076)	(0.085)	(0.104)	(0.122)
5th PIA Quintile	0.263***	0.518***	0.487***	0.440***	0.481***	–0.117	0.155**	–0.139	–0.048	–0.039
	(0.072)	(0.054)	(0.063)	(0.077)	(0.090)	(0.077)	(0.072)	(0.089)	(0.102)	(0.124)
Missing PIA	0.191*	0.219**	0.280***	0.085	0.036	0.061	–0.022	–0.204***	–0.048	–0.214**
	(0.115)	(0.094)	(0.101)	(0.114)	(0.124)	(0.061)	(0.063)	(0.072)	(0.087)	(0.100)
Constant	–4.892***	515.369***	–16.169	–77.206	–29.060**	–4.914***	735.019***	84.283	50.900	–15.606*
	(0.214)	(71.425)	(52.506)	(71.753)	(13.235)	(0.229)	(74.952)	(56.351)	(82.392)	(9.355)
Observations	18,086	58,599	64,272	51,357	55,511	19,458	65,344	77,531	68,436	94,536

(C) Log of Spending

	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
	Men					Women			
	65–69	70–74	75–79	80+		65–69	70–74	75–79	80+
Part B Enrollment	−1.362***	−1.110***	−1.062***	−0.771***		−1.181***	−1.257***	−1.107***	−1.005***
	(0.127)	(0.104)	(0.110)	(0.134)		(0.149)	(0.161)	(0.141)	(0.151)
Age 65	−0.519***					−0.673***			
	(0.045)					(0.037)			
Age	0.984	0.282	−0.282	0.223**		−1.237	−0.276	−0.049	0.366***
	(1.045)	(0.598)	(0.695)	(0.110)		(0.865)	(0.465)	(0.555)	(0.075)
Age Squared (/100)	−0.671	−0.157	0.205	−0.123*		0.961	0.222	0.055	−0.212***
	(0.774)	(0.415)	(0.452)	(0.065)		(0.641)	(0.323)	(0.361)	(0.043)
Ever Married	0.070	0.084	0.186***	0.243***		0.037	0.149***	0.119**	0.141***
	(0.062)	(0.073)	(0.072)	(0.070)		(0.056)	(0.054)	(0.057)	(0.053)
Disabled	0.907***	0.517***	0.404***	0.275***		1.049***	0.755***	0.595***	0.477***
	(0.036)	(0.040)	(0.051)	(0.060)		(0.037)	(0.041)	(0.047)	(0.045)
Death This Year	2.278***	2.187***	2.004***	1.716***		2.498***	2.435***	2.224***	1.721***
	(0.067)	(0.051)	(0.047)	(0.030)		(0.061)	(0.049)	(0.036)	(0.025)
Death Next Year	1.677***	1.504***	1.261***	1.062***		1.971***	1.654***	1.457***	1.049***
	(0.063)	(0.050)	(0.047)	(0.028)		(0.062)	(0.054)	(0.044)	(0.026)
Death After Next Year					*Omitted*				
Less Than High School					*Omitted*				
High School Graduate	0.005	−0.015	0.007	0.020		−0.144***	−0.136***	−0.099***	−0.054**
	(0.034)	(0.033)	(0.034)	(0.033)		(0.025)	(0.025)	(0.024)	(0.025)
Some College	0.055	0.080**	0.030	0.057		−0.056*	−0.065**	−0.029	−0.042
	(0.036)	(0.038)	(0.040)	(0.041)		(0.031)	(0.030)	(0.029)	(0.030)
Bachelor's Degree or Above	−0.012	0.015	0.035	0.141***		−0.088***	−0.066**	−0.031	0.006
	(0.036)	(0.037)	(0.039)	(0.037)		(0.033)	(0.032)	(0.032)	(0.035)
1st PIA Quintile					*Omitted*				
2nd PIA Quintile	−0.268***	−0.107**	−0.105**	−0.121**		−0.096***	−0.080**	−0.057	0.019
	(0.042)	(0.042)	(0.045)	(0.049)		(0.036)	(0.036)	(0.041)	(0.040)
3rd PIA Quintile	−0.223***	−0.065	−0.062	−0.060		−0.151***	−0.115***	−0.034	0.012
	(0.040)	(0.040)	(0.042)	(0.048)		(0.035)	(0.036)	(0.039)	(0.040)
4th PIA Quintile	−0.154***	−0.060	0.034	−0.012		−0.134***	−0.122***	−0.049	0.016
	(0.039)	(0.039)	(0.042)	(0.043)		(0.037)	(0.037)	(0.042)	(0.043)
5th PIA Quintile	−0.109***	0.004	0.015	0.071		−0.128***	−0.076**	−0.041	0.036
	(0.041)	(0.041)	(0.040)	(0.045)		(0.038)	(0.036)	(0.040)	(0.039)
Missing PIA	0.003	0.032	0.030	0.028		−0.030	−0.075**	−0.030	−0.023
	(0.065)	(0.067)	(0.061)	(0.068)		(0.033)	(0.031)	(0.036)	(0.033)
Constant	−27.966	−4.485	17.410	−2.339		47.524	16.285	8.499	−7.822**
	(35.247)	(21.519)	(26.736)	(4.727)		(29.220)	(16.735)	(21.340)	(3.204)
SD of Residuals	1.85	1.84	1.82	1.84		1.72	1.73	1.72	1.88
AR(1) Coefficients	0.396***	0.435***	0.421***	0.387***		0.430***	0.467***	0.435***	0.393***
	(0.006)	(0.005)	(0.006)	(0.005)		(0.006)	(0.005)	(0.005)	(0.005)
Observations	60,457	60,862	50,543	55,327		75,803	79,270	71,068	97,220
R^2	0.104	0.077	0.080	0.107		0.116	0.085	0.090	0.090

Estimates are based on the linked National Health Interview Survey sample, 1994–2005. The sample includes survey respondents age 65 or older linked to the Medicare administrative information between 1994 (or the year they turn 65) and 2005. The models of Medicare spending include beneficiaries with zero months of enrollment in a Medicare Advantage plan (Panels B and C). Additional independent variables include a set of indicator variables for calendar years.

***, $p < 0.01$; **, $p < 0.05$; *, $p < 0.1$.

PIA = primary insurance amount; SD = standard deviation.

Table B4.
Estimated Regression Coefficients, by Service Type

(A) Likelihood of Positive Spending

	(1) Total	(2) Inpatient	(3) PAC	(4) Hospice	(5) Outpatient	(6) Physician	(7) DME
				Men			
Lagged Positive Spending	3.036***	0.961***	1.765***	6.026***	1.783***	2.943***	2.624***
	(0.024)	(0.017)	(0.027)	(0.395)	(0.015)	(0.023)	(0.020)
1st PIA quintile (Omitted)							
2nd PIA quintile	–0.132***	–0.074***	–0.165***	0.084	–0.065***	–0.101***	–0.082***
	(0.038)	(0.023)	(0.031)	(0.077)	(0.022)	(0.034)	(0.025)
3rd PIA quintile	0.099***	–0.063***	–0.226***	–0.005	0.021	0.144***	–0.023
	(0.036)	(0.022)	(0.032)	(0.081)	(0.022)	(0.034)	(0.024)
4th PIA quintile	0.316***	–0.066***	–0.258***	0.081	0.075***	0.370***	–0.031
	(0.039)	(0.023)	(0.031)	(0.082)	(0.023)	(0.037)	(0.025)
5th PIA quintile	0.480***	–0.086***	–0.305***	0.102	0.102***	0.538***	–0.102***
	(0.040)	(0.023)	(0.033)	(0.080)	(0.022)	(0.038)	(0.026)
Missing PIA	0.172***	–0.202***	–0.072	–0.162	–0.014	0.178***	0.076*
	(0.064)	(0.040)	(0.051)	(0.133)	(0.034)	(0.060)	(0.041)
				Women			
Lagged Positive Spending	3.319***	1.046***	1.789***	5.780***	1.854***	3.159***	2.296***
	(0.029)	(0.013)	(0.021)	(0.218)	(0.015)	(0.026)	(0.015)
1st PIA quintile (Omitted)							
2nd PIA quintile	–0.105**	–0.074***	–0.041	–0.077	–0.062***	–0.079*	–0.028
	(0.051)	(0.024)	(0.030)	(0.083)	(0.022)	(0.046)	(0.024)
3rd PIA quintile	–0.104**	–0.071***	–0.111***	–0.009	–0.075***	–0.091**	–0.101***
	(0.049)	(0.023)	(0.030)	(0.087)	(0.023)	(0.044)	(0.025)
4th PIA quintile	–0.064	–0.069***	–0.111***	–0.071	–0.080***	–0.026	–0.073***
	(0.051)	(0.023)	(0.031)	(0.091)	(0.024)	(0.048)	(0.025)
5th PIA quintile	–0.004	–0.128***	–0.150***	0.022	–0.072***	0.025	–0.145***
	(0.053)	(0.024)	(0.032)	(0.091)	(0.025)	(0.050)	(0.025)
Missing PIA	–0.115***	–0.061***	0.024	0.041	–0.097***	–0.137***	0.003
	(0.044)	(0.020)	(0.026)	(0.073)	(0.019)	(0.040)	(0.020)

(B) Log of Spending

	(1) Total	(2) Inpatient	(3) PAC	(4) Hospice	(5) Outpatient	(6) Physician	(7) DME
				Men			
1st PIA quintile (Omitted)							
2nd PIA quintile	–0.158***	–0.083***	–0.025	0.107	–0.039*	–0.134***	0.011
	(0.025)	(0.017)	(0.035)	(0.083)	(0.023)	(0.022)	(0.042)
3rd PIA quintile	–0.112***	–0.023	–0.135***	0.080	–0.064***	–0.039*	–0.051
	(0.024)	(0.017)	(0.035)	(0.086)	(0.023)	(0.020)	(0.039)
4th PIA quintile	–0.062**	–0.009	–0.163***	–0.106	–0.070***	0.034*	–0.097**
	(0.024)	(0.017)	(0.037)	(0.086)	(0.022)	(0.021)	(0.039)
5th PIA quintile	–0.014	0.004	–0.132***	0.001	–0.032	0.102***	–0.155***
	(0.025)	(0.017)	(0.038)	(0.082)	(0.022)	(0.021)	(0.039)
Missing PIA	0.018	0.015	0.051	0.285**	0.060*	0.084**	0.151**
	(0.039)	(0.024)	(0.056)	(0.142)	(0.034)	(0.034)	(0.066)
				Women			
1st PIA quintile (Omitted)							
2nd PIA quintile	–0.063***	0.008	–0.032	0.032	–0.055***	–0.039**	0.006
	(0.022)	(0.017)	(0.031)	(0.097)	(0.019)	(0.019)	(0.036)
3rd PIA quintile	–0.084***	–0.018	–0.056*	0.121	–0.056***	–0.049***	–0.077**
	(0.022)	(0.016)	(0.030)	(0.095)	(0.019)	(0.019)	(0.036)
4th PIA quintile	–0.083***	–0.002	–0.016	0.038	–0.090***	–0.035*	–0.045
	(0.023)	(0.018)	(0.034)	(0.093)	(0.020)	(0.020)	(0.038)
5th PIA quintile	–0.059***	0.017	–0.036	0.145	–0.079***	0.030	–0.178***
	(0.022)	(0.018)	(0.033)	(0.101)	(0.020)	(0.019)	(0.037)
Missing PIA	–0.045**	–0.004	0.027	0.075	–0.008	–0.043***	0.033
	(0.019)	(0.014)	(0.027)	(0.081)	(0.017)	(0.016)	(0.032)

The estimates are based on the linked NHIS sample, 1994–2005. The sample includes survey respondents age 65 or older linked to the Medicare administrative information between 1994 (or the year they turn 65) and 2005 and with zero months of enrollment in an MA plan. Additional independent variables includes an indicator variable for age 65, age, age squared, an indicator variable for Part B enrollment, an indicator variable for marital status, an indicator variable for disability, a set of indicator variables for time until death, a set of indicator variables for educational attainment, and a set of indicator variables for calendar years.

***, $p < 0.01$; **, $p < 0.05$; *, $p < 0.1$.

DME = durable medical equipment; PAC = post–acute care; PIA = primary insurance amount; SD = standard deviation.

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