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DOES MEDICARE BENEFIT THE POOR? NEW ANSWERS TO AN OLD QUESTION

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ABSTRACT

Previous research has found that Medicare benefits flow primarily to the most economically advantaged groups and that the financial returns to Medicare are consequently higher for the rich than for the poor. Taking a different approach, we find very different results. According to the Medicare Current Beneficiary Survey, the poorest groups receive the most benefits at any given age. In fact, the advantage of the poor in benefit receipt is so great that it easily overcomes their higher death rates. This leads to the result that the financial returns to Medicare are actually much higher for poorer groups in the population and that Medicare is a highly progressive public program. These new results appear to owe themselves to our measurement of socioeconomic status at the individual level, in contrast to the aggregated measures used by previous research.

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1 Introduction

Medicare is one of the most significant public entitlement programs in the United States, and certainly the most important program in health. In 1998, Medicare benefit payments alone accounted for 13% of the Federal budget and 2.5% of GDP (US Department of Health and Human Services, 1999). The sheer size of Medicare makes it important for us to understand and quantify its value. In particular, we need to know about the distribution of Medicare benefits and costs, whether Medicare actually benefits anyone, and if so whom.

Though Medicare's primary financing mechanism involves substantial intergenerational transfers of income,[1] whether Medicare has actually benefited particular groups in a cohort depends also on how it redistributes money within generations. Medicare may have improved the lot of the average person in today's elderly cohorts, but not necessarily the lot of the average poor person or the average rich person. It is clear that Medicare taxation transfers resources from the rich to the poor. However, a great deal of previous research has argued that Medicare's benefit structure undoes this by transferring resources back to the rich (Long and Settle, 1984; Gornick et al., 1996; McClellan and Skinner, 1997). This research finds that the poor use fewer Medicare resources at any given age, and that their earlier mortality further deprives them of Medicare benefits.[2]

In this paper, we present some new evidence on socioeconomic status and Medicare benefits, and we reach very different conclusions. We find that Medicare spends far more

[1]The two primary mechanisms by which Medicare effects intergenerational transfers are variations in cohort size and growth in medical care expenditures over time. Since the introduction of Medicare, expenditures per beneficiary have grown nearly 4% per annum, as documented in footnote 10.

[2]This research mirrors analogous literature on the progressivity of Social Security. The early literature on this topic (Burkhauser and Warlick, 1981; Hurd and Shoven, 1985; Boskin and Puffert, 1988; Duggan et al., 1993) ignores the lower mortality rates faced by members of disadvantaged groups. Shoven et al. (1987) find that the progressivity of Social Security is considerably flattened when the differential mortality of smokers is taken into account. Similarly, Garrett (1995) finds that differences in mortality between the poor and rich eliminates the "progressive spread in returns" to Social Security across income categories.

on the poor than on the rich at any given age. Reversing the direction of the relationship between socioeconomic status and Medicare benefits has a huge impact on the evaluation of Medicare as a welfare program. In particular, we calculate that the net actuarial value of the Part A benefits received by the 1931-41 birth cohort was much higher for the poor than for the rich. While Medicare is actuarially unfair for college graduates, high school dropouts almost double their money. This is in contrast to previous research, which has found that the actuarial value of Medicare is much higher for the rich, or that Medicare results in a lifetime financial transfer from poor to rich. Even after accounting for the extra access to insurance that Medicare provides the poor, this research has found it at best equally beneficial for rich and poor groups (McClellan and Skinner, 1997).

Unlike much of the previous literature, we use an individual's own educational attainment as a measure of socioeconomic status. In contrast, other researchers have used average income in an individual's area of residence. We find evidence that aggregation bias may be the reason for the discrepancy between the two methods. In a single data set where less educated individuals consume far more Medicare benefits than the more educated, individuals who live in richer areas still appear to receive more benefits than those who live in poorer areas. This could be because people with high demands for medical care have incentives to move to richer areas, where medical care may be of higher quality. As a result, more benefits may be paid in richer areas, even if richer individuals themselves are not receiving more.

2 A Framework for Analyzing Progressivity

To analyze the welfare effects of Medicare for different socioeconomic groups, we first have to identify what we mean by socioeconomically advantaged and disadvantaged. We argue that an individual's own educational attainment is a useful way to identify the disadvantaged. We then present a simple framework for estimating the financial returns to Medicare for each group.

2.1 Measuring Socioeconomic Status

Conceptually, socioeconomic status ought to be measured using permanent income, which is the closest thing economists have to a definition of socioeconomic status. Ideally, we would like to study how Medicare benefits vary across permanent income levels. Unfortunately though, permanent income is unobserved, and only its correlates are available for analysis.

One often-used correlate is the average income in an individual's zip code or area of residence. This avoids many of the problems associated with measurement using current-period income by smoothing out life-cycle and idiosyncratic fluctuations in income, but it introduces the possibility of aggregation bias (Geronimus et al., 1996). There are at least two issues to consider. First, richer areas may have higher quality medical facilities.[3] People with high demands for medical care thus have incentives to move to such areas, holding their permanent income constant. Even if individual wealth has no effect on health expenditures, health expenditures could be higher in wealthier areas. Second, richer areas will tend to be older, for life-cycle income reasons, even though this may not reflect differences in permanent income. Since older people have higher demands for medical care, this too can create a positive relationship between health expenditures and area wealth. Several previous studies have found a positive relationship between Medicare expenditures and area income (cf. Long and Settle, 1984; McClellan and Skinner, 1997). Is this an artifact of aggregation bias, or do

[3] For example, Chandra and Skinner (2002) show that areas with a higher percentage of white residents are likely to have higher quality medical facilities.

wealthier people actually cost Medicare more?

One way to assess this is to measure SES at the individual level. Unfortunately, an individual's current-period income is a rather poor measure of permanent income, because it is subject to idiosyncratic and life-cycle fluctuation. A more theoretically sound measure is an individual's educational attainment. An individual's permanent income is generated by the returns to human and nonhuman wealth. Human wealth consists of schooling and unobserved ability. A great deal of research in labor economics suggests that schooling is a very good measure of human wealth, and that unobserved ability is not a very significant component (cf, Card, 1995). In addition, the vast majority of aggregate wealth in the economy is human wealth (Jorgenson and Fraumeni, 1995). Brown and Weisbenner (2002) find that life-cycle (labor) income is three times more important than bequests and inter vivos transfers, which account for 20 to 25% of aggregate wealth. Moreover, even this amount is concentrated among a relatively small percentage of households. Since schooling is perhaps the best feasible measure of human wealth, and since human wealth makes up the majority of total lifetime wealth, schooling is a reasonable way to measure permanent income and SES at the individual level.

2.2 Measuring the Returns to Medicare

Define B_{it} as the Medicare benefits received by the average individual in group i at age t and define τ_{it} as the Medicare taxes paid by i at t. Finally, define S_{it} as the probability that i survives to age t. If the real rate of interest is r, the expected net present value of Medicare transfers to i at age 18 is equal to:

$$\sum_{t \geq 18} S_{it} \frac{(B_{it} - \tau_{it})}{(1+r)^{t-18}} \tag{2.1}$$

This expression is not exactly identical to the welfare benefits of Medicare to i, but it is related. McClellan and Skinner (1997) find that considering only the pure dollar transfers of Medicare understates the relative benefit to the poor, who disproportionately benefited from the increased access to insurance provided by Medicare. Therefore, if the absolute dollar transfers favor the poor, it is likely that they disproportionately benefit in terms of welfare also.

Rewriting equation (2.1) provides us with another useful analytic tool, the internal rate of return. This is the scalar ρ that solves the following equation:

$$\sum_{t \geq 18} S_{it} \frac{(B_{it} - \tau_{it})}{(1+\rho)^{t-18}} = 0 \tag{2.2}$$

The internal rate of return on Medicare is the real rate of interest that would have to obtain in order to set the net present dollar value of Medicare to zero. Conceptually, the internal rate of return would tell us everything we need to know about welfare if a complete private market for old-age medical insurance existed without Medicare. In other words, if people could buy policies when young and receive benefits when old, the private market would price these policies such that their internal rate of return equaled the real rate of interest: this would be the zero profit condition. Therefore, abstracting from the market incompleteness that might generate an insurance value of Medicare, individual i derives a welfare benefit from Medicare if his internal rate of return on it exceeds the real rate of interest, commonly estimated at around 3% per annum (Siegel, 1992). Since Medicare most likely did help to complete the market for old-age medical insurance (McClellan and Skinner, 1997), the simple calculation probably understates the relative welfare benefits of Medicare for the poor.

Estimating the net present value and the internal rate of return of Medicare for different education groups requires that we calculate a survival profile S_{it}, a benefits profile B_{it}, and a tax profile τ_{it} for different socioeconomic groups i. The next few sections document our estimates for these three quantities. We will confine our analysis to the hospital insurance component, or Part A, of Medicare, since it is easy to identify the payroll taxes that fund this program. However, we estimate the educational gradient in total Medicare benefits and find that it is quite similar.

3 Mortality and Socioeconomic Status

Standard life tables tend not to report survival probabilities by education group. Therefore, to calculate S_{it} for different education groups i, we start with standard Social Security Administration life-tables and adjust them to reflect mortality differences across education groups. Using microdata from the National Mortality Followback Surveys of 1986 and 1993, we calculate the ratio of the group-specific death rate to the total death rate. Applying this ratio to the overall life-table then allows us to compute group-specific survival probabilities.

We construct a 1990 period life table for each sex and education group.[4] The 1990 US Vital Statistics period life table gives us a series $\bar{S}_t$, the average probability of survival to age t. Using data from the 1993 National Mortality Followback Survey (NMFS), we then estimate $\frac{S_{it}}{\bar{S}_t}$ for several age groups. The NMFS contains individual-level data on a sample

[4]Since we are calculating the rate of return for a specific birth cohort, the best thing to do would be to construct a cohort life table, but we know of no source for cohort-specific death rates by education group. Since mortality rates declined more rapidly among the rich from 1960 onwards (Feldman et al., 1989), it is likely that this strategy will understate the progressivity of Medicare.

of decedents from 1992. It is designed to be nationally representative, while oversampling young decedents. Based on interviews with next-of-kin, the NMFS collects demographic information about each decedent, including age, sex, race, education, smoking status, and cause of death. Using the weights provided in the NMFS, we are able to estimate the total number of deaths nationwide within each age group, and within each age-education category. To translate the total number of deaths into death rates, we use the National Health Interview Survey to estimate the 1992 population nationwide in each age-education category. The results of these calculations are shown in Table 1. With only a few exceptions, death rates decline uniformly with education group, within an age category. Among very old women, we observe a slight increase in mortality rates between high school dropouts and high school graduates. Among 45-54 year-old men and 55-64 year-old women, we observe mortality rates that are higher for college attendees than high school graduates. Apart from these isolated cases, mortality rates fall with education.

The associated survival curves are graphed in Figures 1 and 2, for men and women. For both men and women, 18 year-old high school dropouts are less likely to reach age 65 than college graduates (or those who will end up as college graduates). However, the difference is twice as large for men as for women. High School dropout males are twenty percentage points less likely to survive to age 65, while females are only about ten percentage points less likely. This is one of the reasons why, from an individual perspective, Medicare is a much better deal for low-skill women than for low-skill men.

Table 1: Yearly Deaths per 1000 people, by Age, Sex, and Education, 1985-92.

	Age Group	Less than High School	Graduate of High School	Attended College	Graduate of College	Overall
Males	18-24	2.36	1.98	0.88	0.46	1.60
	25-34	3.83	2.03	1.40	0.67	1.82
	35-44	5.00	3.28	2.61	1.23	2.73
	45-54	9.45	5.50	6.03	2.80	5.62
	55-64	17.47	13.70	12.46	7.43	13.38
	65-74	35.23	33.69	26.13	16.94	30.33
	75+	100.94	95.32	78.02	69.99	92.97
Females	18-24	0.63	0.54	0.36	0.21	0.47
	25-34	1.40	0.67	0.50	0.33	0.65
	35-44	1.98	1.48	0.89	0.88	1.27
	45-54	4.69	3.30	2.17	1.50	3.00
	55-64	10.33	7.58	7.80	5.45	8.13
	65-74	18.65	19.66	15.43	11.82	17.82
	75+	75.88	83.12	73.65	49.05	74.91

Note: Death rates are averages of 1985 and 1992 rates, estimated from the 1986 and 1993 National Mortality Followback Surveys, respectively.

Figure 1: Male Survival Curves by Education.

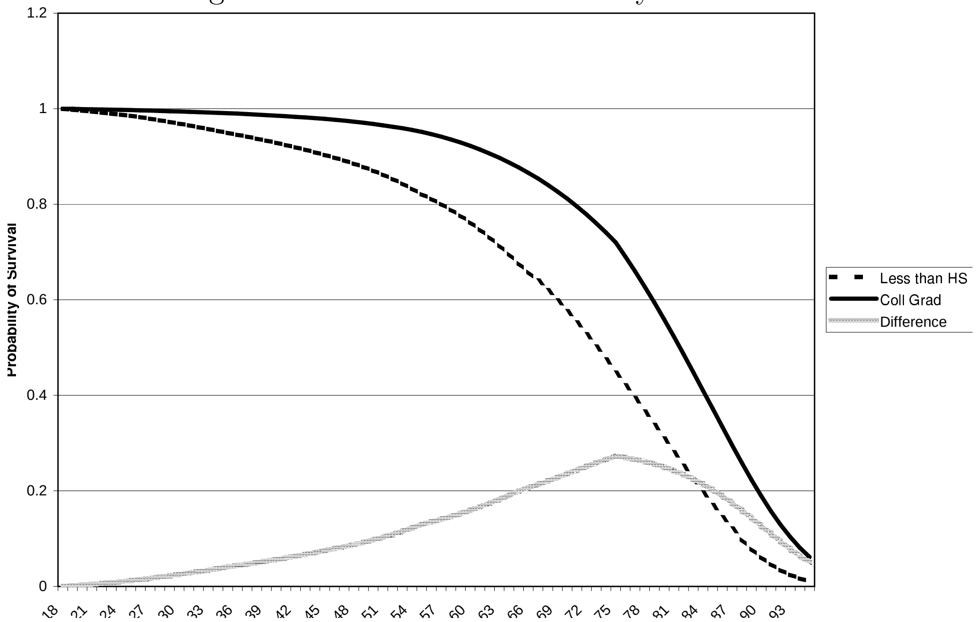
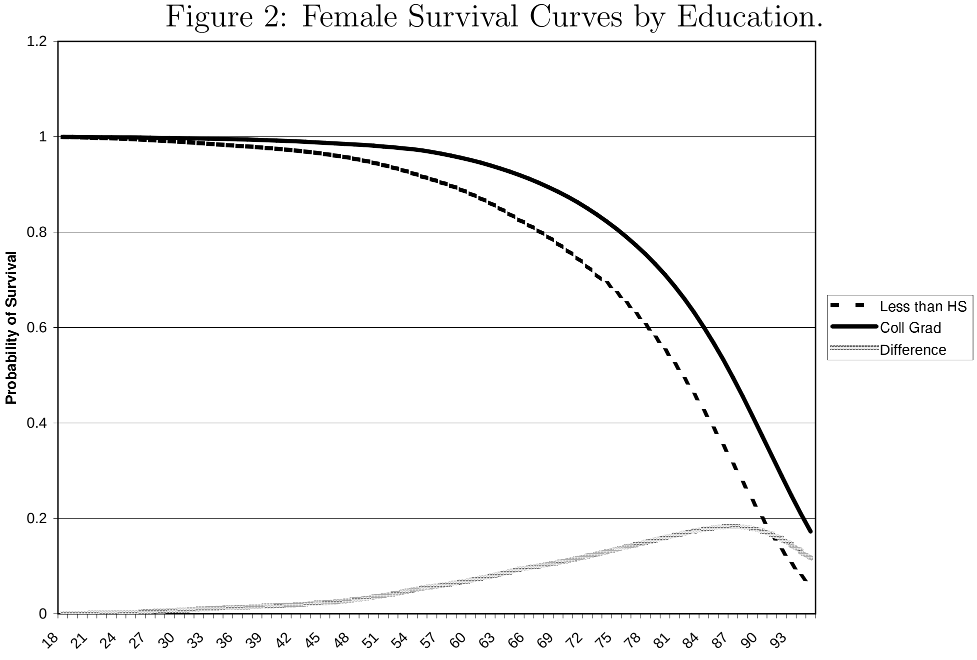


Figure 2: Female Survival Curves by Education.



4 The Incidence of Medicare Benefits

We calculate age-specific Medicare benefits, B_{it} using the Medicare Current Beneficiary Survey (MCBS). This is a nationally representative, longitudinal, random sample of Medicare beneficiaries, and it includes extensive information about Medicare expenditures, along with demographic information, such as about years of schooling and geographic information.

4.1 Age-specific Medicare Expenditures

The MCBS Cost and Use Files are nationally representative data sets designed to ascertain utilization and expenditures for the Medicare population. They are available every year from 1992 to 1998. The sample frame consists of aged and disabled beneficiaries enrolled in Medicare Part A and/or Part B although we use only the aged. The disabled (under 65 years of age) and the oldest-old (85 years of age or over) are oversampled. The MCBS contains demographic data such as age, sex, race, and educational attainment, along with state, county, and zip code of residence. It also contains detailed self-reported information on health, including the prevalence of various conditions, measures of physical limitation in performing daily activities (ADLs) and instrumental activities of daily living (IADLs), and height and weight.

Table 2 presents average real per capita Medicare benefits by age group, sex, and educational attainment.[5] As described in Appendix A, these data are all deflated using the Geographic Practice Cost Indices (GPCI) and the hospital wage-price indices, to account for regional differences in the price of medical care. The top panel of the table shows the educational gradient in total Medicare benefits, which equals Medicare Parts A and B fee-for-

[5] Appendix A describes how expenditure data are collected in the MCBS, and how we identify Part A and B expenditures.

Table 2: Real Per Capita Medicare Benefits by Educational Attainment.

		Females				Males			
		High Sch Dropouts	High Sch Grads	College Attendees	College Grads	High Sch Dropouts	High Sch Grads	College Attendees	College Grads
Total Medicare	65-74	$4,455	$3,363	$3,232	$2,366	$4,941	$3,908	$3,794	$3,407
	75-84	$6,001	$5,310	$5,433	$4,478	$6,361	$6,051	$6,315	$5,573
	85+	$7,565	$6,765	$5,717	$5,915	$7,323	$7,565	$7,561	$6,170
Medicare Part A	65-74	$2,574	$1,733	$1,612	$892	$2,990	$2,101	$1,891	$1,737
	75-84	$3,786	$3,112	$3,171	$2,450	$3,783	$3,590	$3,461	$2,974
	85+	$5,290	$4,547	$3,609	$3,974	$4,937	$5,184	$5,208	$3,590
Medicare Part B	65-74	$1,535	$1,173	$1,092	$1,035	$1,494	$1,309	$1,217	$1,199
	75-84	$1,814	$1,630	$1,629	$1,515	$1,930	$1,795	$2,096	$2,005
	85+	$1,868	$1,711	$1,576	$1,587	$1,776	$1,770	$1,728	$1,890
Medicare HMO	65-74	$346	$459	$529	$440	$464	$507	$696	$479
	75-84	$405	$568	$635	$513	$648	$666	$757	$595
	85+	$406	$507	$532	$353	$621	$610	$625	$690

Source: MCBS, 1992-1998.

Notes: All values are per capita real 1997 dollars and are deflated by the Geographic Practice Cost Index for the relevant county and year.

service expenses, plus payments made by Medicare on behalf of its beneficiaries to Medicare HMO's.[6]

In these data, there are consistent negative gradients in education (that is, low SES individuals spent more per capita than high SES individuals). The difference between high school dropouts and college graduates is always at least ten percent (for 75-84 year-old women) and reaches as high as forty-five percent for 65-74 year old men. In addition, there are few instances of increases in per capita benefits across education levels. Per capita benefits rise with education only four out of eighteen times, and two of these times involve differences of $120 or less, or about three percent. Most of the negative gradient is driven by variation in Part A, or hospital insurance benefits. There is also a consistent negative gradient in Part B benefits, but not as large in magnitude. If anything, there is a positive gradient in Medicare HMO payments, although these make up a rather small share of total Medicare benefits.

Part, though not all, of the negative gradient in Medicare benefits is explained by differences in health status. Including self-reported occurrence of diseases and disability in the MCBS erases more than half of the gradient between high school dropouts and college graduates. The rest could be generated by variation in unobserved health, but it could also be related to differences in private insurance coverage and other factors. (Not surprisingly, there is a positive gradient in privately financed medical expenditures, once one controls for health.) A definitive explanation for the relationship between education and Medicare benefits, however, is beyond the scope of this paper.

[6] We do not include medical expenditures paid by the HMO's themselves, because this would be double-counting. The actual payment made by Medicare to the HMO represents the public liability. Any difference between these payments and HMO expenditures represent profit or loss for the private firms, not public liability for old-age medical care.

Table 3: Changes over time in real per capita Medicare benefits by Educational Attainment.

		Females				Males			
		High Sch Dropouts	High Sch Grads	College Attendees	College Grads	High Sch Dropouts	High Sch Grads	College Attendees	College Grads
	1992	$4,817	$3,742	$3,597	$3,141	$4,770	$4,152	$4,010	$4,020
	1993	$5,047	$3,874	$3,775	$3,297	$5,733	$4,177	$4,294	$4,211
	1994	$5,476	$4,181	$4,011	$3,494	$5,882	$4,544	$3,918	$4,085
	1995	$6,301	$4,729	$4,833	$3,325	$5,170	$4,875	$4,688	$3,520
	1996	$5,947	$4,383	$4,537	$3,728	$6,609	$4,570	$5,067	$3,912
	1997	$6,128	$4,353	$4,591	$3,704	$5,743	$5,427	$6,261	$4,623
	1998	$5,432	$4,740	$3,924	$3,677	$6,202	$5,176	$4,732	$4,430
1992	65-74	$3,953	$2,930	$2,865	$1,721	$4,092	$3,633	$3,517	$3,676
	75-84	$5,080	$4,643	$5,046	$4,809	$5,438	$5,216	$4,459	$4,847
	85+	$6,648	$6,609	$3,778	$6,087	$6,269	$5,327	$7,937	$4,605
1998	65-74	$4,415	$2,985	$2,780	$2,283	$5,147	$3,241	$2,621	$3,452
	75-84	$5,234	$4,898	$5,310	$4,663	$6,365	$6,094	$7,733	$6,115
	85+	$6,333	$6,725	$5,405	$4,414	$6,873	$4,691	$6,839	$5,146

Source: 1992-8 MCBS.

Note: All data are in real per capita 1997 dollars and are adjusted using the GPCI.

Table 3 demonstrates that high school dropouts enjoyed larger increases in benefits than college graduates during the early 1990s, a result that is consistent with the findings of Lee et al. (1999). However, the middle and bottom panels also show that consistent negative gradients in benefits existed as early as 1992 and widened even further over time. This contrasts sharply with studies that examine gradients in Medicare expenditures by zip code income. These studies, such as Lee et al. (1999), find substantially positive gradients in 1990, and did not turn consistently negative even by 1995.[7]

4.2 Lifetime Medicare Benefits

Medicare hospital insurance (Part A) is funded entirely by Medicare payroll taxes. On the other hand, Part B is funded by general federal revenue and beneficiary premia. Therefore, the financial return on lifetime payroll taxes is equal to expected lifetime Medicare Part

[7]Lee, McClellan and Skinner, for instance, find flat or slightly positive gradients for men aged 65-74 and 75-84.

A benefits. HMO beneficiaries present a complication, because Medicare pays a flat fee to private HMO's, who in turn provide hospital insurance as well as insurance for items that would normally be covered by Part B. To decompose HMO payments, we assume that HMO patients within an age, sex, and education category spend the same proportion of resources on Part A services as fee-for-service patients in the same category.[8] This is taken to be the proportion of the HMO premium allocated to Part A.

Applying the survival profiles estimated earlier to the Part A benefits profile in the MCBS yields an estimate of expected lifetime Part A benefits.[9] This provides us with a cross-section of Medicare benefits, but we are interested in calculating the lifetime benefits of the 1931-41 birth cohort. This is an important distinction, since real Medicare benefits tend to grow. Therefore, we calculate the expected value of Medicare benefits under various assumptions about future real growth in Medicare benefits.

To obtain a more accurate lifetime benefit profile, we calculate benefits for smaller age intervals: 65-69, 70-74, 75-79, 80-84, and 85+. Within each interval, real benefits are assumed to be equal at a given point in time. For the sake of comparison, we recalculate the expected net present value of Medicare benefits assuming different annual real rates of benefit growth. For example, if we assume that benefits grow at $X\%$, we take the cross-sectional benefit figures and adjust them according to $B_{it} * (1 + \frac{X}{100})^{t-65}$. In other words, the benefits for 70 year-olds are assumed to have been growing for 5 years, and so on. The logic behind this framework is that the 1931-41 birth cohort is entering Medicare eligibility during the MCBS period. Therefore, it is roughly accurate to regard the MCBS as recording average benefits

[8]Roughly two-thirds of Medicare expenditures go to Part A services.

[9]We do not deflate the benefit data using the GPCI or wage-price indices for the purposes of this calculation, because we are concerned with actual dollars received, in comparison to actual dollars paid. In practice, however, deflating the benefit data further strengthens Medicare's estimated progressivity.

Table 4: Expected Net Present Value of Medicare Benefits, by Sex and Education.

	Real Interest Rate	Male Less than HS	Male HS Grad	Male Coll Attendee	Male Coll Grad	Female Less than HS	Female HS Grad	Female Coll Attendee	Female Coll Grad
No Growth	0%	$45,215	$46,988	$49,105	$50,067	$41,463	$42,277	$43,008	$40,848
	1%	$25,563	$26,128	$27,306	$27,614	$22,970	$23,186	$23,596	$22,014
	2%	$14,606	$14,688	$15,355	$15,403	$12,876	$12,866	$13,094	$12,005
	3%	$8,430	$8,344	$8,727	$8,687	$7,301	$7,221	$7,346	$6,622
	4%	$4,913	$4,788	$5,012	$4,951	$4,185	$4,098	$4,166	$3,694
	5%	$2,890	$2,775	$2,907	$2,850	$2,425	$2,351	$2,386	$2,084
4% Ann. Growth	0%	$71,399	$79,210	$83,026	$87,438	$71,556	$75,719	$76,671	$78,149
	1%	$39,508	$43,117	$45,136	$47,150	$38,670	$40,558	$41,132	$41,188
	2%	$22,113	$23,740	$24,829	$25,726	$21,157	$21,987	$22,327	$21,965
	3%	$12,513	$13,216	$13,815	$14,199	$11,715	$12,060	$12,260	$11,849
	4%	$7,157	$7,437	$7,772	$7,925	$6,563	$6,692	$6,807	$6,466
	5%	$4,135	$4,229	$4,420	$4,471	$3,718	$3,755	$3,821	$3,567

that will be received at the time of entry into Medicare, and to inflate benefits accordingly. We explore the impact of real benefit growth that ranges from zero to four percent annually, since the latter figure has been the benefit growth rate that Medicare has experienced since its introduction.[10]

Table 4 documents the results of the lifetime benefit calculation, for various real interest rates and real benefit growth rates. Adjusting for survival, and accounting for benefit growth favors the more educated groups, because of their greater longevity. However, even after accounting for longevity differences, male high school dropouts are only at a slight disadvantage, receiving 12% fewer lifetime benefits than college graduates at a 3% real rate of interest and 4% real rate of benefit growth. Female high school dropouts are just about level with the other groups. In contrast, high school dropouts earn about half as much as college graduates, so (as we will confirm) the gradient in lifetime taxes paid will be substantially steeper. As we will see below, Table 4 turns out to be the reason why our conclusion

[10] Data from the Health Care Financing Administration (http://www.hcfa.gov/stats/hstats98/blustat4.htm, downloaded on March 8, 2002) on total Medicare outlays and total Medicare enrollees, shows that per capita benefits grew four percent annually from 1966-2000.

that Medicare transfers resources to the poor is robust to a variety of different estimation assumptions. No matter how one assembles the data, there is too little variation across education groups in lifetime Medicare benefits to support any other conclusion.

5 The Lifetime Incidence of Medicare Taxation

To estimate τ_{it}, expected Medicare taxes paid by group i at time t, we use data on actual Medicare tax rates, and earnings data from the Health and Retirement Study (HRS) to construct the expected lifetime tax liability of the 1931-1941 birth cohort.[11] The HRS is a nationally-representative longitudinal household dataset with detailed demographic and financial data on respondents. We use a restricted version of the HRS that links respondent information to the actual Social Security earnings records so that we can measure payroll taxes paid with minimal error. In particular, for 9537 of the 13,478 people present in Wave 1 of the HRS, we have the quarterly earnings subjected to Social Security taxation from 1951 to 1991. Over this period of time, the earnings subjected to Medicare taxation was identical. From 1991 to 1999, we have detailed data on wage and self-employment earnings from the HRS itself.[12]

There are two important problems to solve in these data. First, even though the males in this cohort have much higher labor force attachment and much higher payroll tax outlays, it would be misleading to allocate all of this to men. If market and home work are shared within a family, so too are market wages and market taxes. Therefore, taxes should be calculated for married couples rather than individual workers. The HRS eases this task

[11]Since we are evaluating the Part A hospital insurance component of Medicare, we restrict ourselves to Medicare payroll taxes, which are the sole source of funds for Part A coverage.

[12]Details on the construction of earnings and taxes are presented in Appendix B.

Table 5: Expected Net Present Value of Tax Liability faced by Families of HRS Cohort Members.

Real Interest Rate	Male: Less than HS	Male: HS Grad	Male: Coll Attendee	Male: Coll Grad	Female: Less than HS	Female: HS Grad	Female: Coll Attendee	Female: Coll Grad
0%	$20,298	$28,676	$32,385	$45,565	$15,406	$24,007	$29,059	$35,777
1%	$14,971	$20,983	$23,485	$32,393	$11,458	$17,743	$21,235	$25,659
2%	$11,165	$15,534	$17,233	$23,298	$8,612	$13,256	$15,695	$18,621
3%	$8,417	$11,633	$12,793	$16,953	$6,540	$10,009	$11,731	$13,672
4%	$6,413	$8,810	$9,607	$12,481	$5,016	$7,635	$8,864	$10,155
5%	$4,937	$6,745	$7,296	$9,296	$3,884	$5,883	$6,770	$7,629

Note: All figures are in real 1997 dollars, from the perspective of an 18 year-old in the HRS cohort.

considerably, because it contains earnings histories for many married couples, but we are left with the task of estimating the family's tax burden for some families that dissolved due to divorce and death. Second, the HRS does not separate taxable wage income from taxable self-employment income, even though the two income sources were taxed at different rates for much of Medicare's history. We thus need some way of estimating the share of income from self-employment earnings. Both these issues force us to impute portions of data for a relatively small piece of the HRS sample. In appendix B, we discuss in detail the imputation procedures used to address these two problems.

Based on historical tax rates, we can estimate taxes paid using earnings data from the HRS. All these calculations result in an age-profile of real Medicare income (i.e., income subject to Medicare taxes) for couples, as well as age-profiles of real Medicare taxes paid, by education group. Using our estimated survival curves, we can thus calculated the expected net present value of a family's Medicare tax liabilities across education groups and sex. When we report the tax liabilities of a man (or a woman), we are reporting the liability faced by the family of the average man (or woman) in that category. On average, the families of college graduates can expect to pay about twice as much in Medicare payroll taxes as the families of high school dropouts. This result was quite insensitive to various manipulations of our assumptions about self-employment income or the imputation of spousal income.

Notice also that the families of women are expected to have fewer liabilities than the families of men. This result is due almost entirely to the timing of Medicare for the HRS cohort. Since women tend to have older spouses, their families' income profiles peak earlier. Therefore, they earned a larger portion of their lifetime income before the introduction of Medicare taxes in 1966. When we calculated what expected tax liabilities would have been if Medicare had been introduced in 1950, most of this gap disappeared.

6 The Returns to Medicare

To arrive at final dollar returns from Medicare, we have to reconcile the tax liabilities of families, in Table 5 with the expected medical benefits of individuals, in Table 4. Our strategy is to convert the data on individual medical benefits to family benefits by matching men and women. We assume that families are formed at marriage and dissolved only at the death of one spouse. To compute the average family Medicare benefit for, say, X year-old college-educated males, we use the proportion of this population that has a living spouse or ex-spouse, along with the distribution of spousal education for 65 year-old college-educated males in the HRS. The average Medicare family benefit is then equal to the individual's benefit plus the average spousal benefit. The latter term is taken to be the probability of having a living spouse within the age-sex-education cell, multiplied by the weighted average of Medicare benefits for X year-old females, where the weights are given by the distribution of spousal education observed for 65 year-old college-educated males in the HRS.

After converting Table 4 to a family basis, we can compute the expected dollar value

Table 6: Expected Net Present Dollar Flows from Medicare for Families of HRS Cohort Members, by sex and education of the cohort member.

	Real Interest Rate	Male: Less than HS	Male: HS Grad	Male: Coll Attendee	Male: Coll Grad	Female: Less than HS	Female: HS Grad	Female: Coll Attendee	Female: Coll Grad
No Growth	0%	$38,340	$34,245	$32,891	$18,024	$59,260	$54,643	$52,499	$47,178
	1%	$18,656	$14,853	$13,690	$3,421	$31,403	$26,884	$25,031	$21,049
	2%	$8,317	$5,087	$4,149	-$2,918	$16,239	$12,322	$10,817	$7,946
	3%	$2,982	$351	-$377	-$5,239	$8,009	$4,795	$3,612	$1,590
	4%	$320	-$1,777	-$2,329	-$5,681	$3,582	$1,015	$99	-$1,303
	5%	-$923	-$2,579	-$2,992	-$5,311	$1,243	-$781	-$1,484	-$2,446
4% Ann Growth	0%	$75,587	$77,126	$77,101	$66,803	$105,514	$109,448	$109,991	$110,320
	1%	$38,868	$38,052	$37,680	$29,635	$56,577	$56,543	$56,112	$55,035
	2%	$19,389	$17,752	$17,287	$11,297	$30,069	$28,518	$27,773	$26,404
	3%	$9,103	$7,330	$6,883	$2,539	$15,677	$13,719	$12,946	$11,703
	4%	$3,736	$2,102	$1,719	-$1,388	$7,872	$5,976	$5,284	$4,287
	5%	$1,001	-$403	-$715	-$2,920	$3,665	$2,000	$1,421	$670

Note: All figures are in real 1997 dollars, from the perspective of an 18 year-old in the HRS cohort.

Table 7: Internal rates of return on Medicare by sex, education group, and rates of growth in Medicare benefits.

Ben. Gwth.	Males: HS Dropout	Males: HS Grad	Males: Coll Attendee	Males: Coll Grad	Males: Overall	Females: HS Dropout	Females: HS Grad	Females: Coll Attendee	Females: Coll Grad	Females: Overall
0%	4.8%	3.6%	3.4%	2.3%	3.7%	4.8%	3.4%	3.0%	2.2%	3.6%
1%	5.1%	4.0%	3.8%	2.8%	4.1%	5.1%	3.8%	3.4%	2.6%	4.0%
2%	5.4%	4.4%	4.2%	3.3%	4.4%	5.4%	4.1%	3.7%	3.1%	4.4%
3%	5.8%	4.8%	4.6%	3.7%	4.8%	5.7%	4.5%	4.1%	3.5%	4.7%
4%	6.1%	5.2%	5.0%	4.2%	5.2%	6.1%	4.9%	4.5%	4.0%	5.1%
5%	6.4%	5.5%	5.4%	4.6%	5.6%	6.4%	5.3%	4.9%	4.4%	5.5%

(benefits minus costs) from Medicare for the families of people of a specific sex and educational attainment. The net flows of Medicare resources are depicted in Table 6. Given a real rate of interest at 2% or higher, the net dollar flows are much higher to the least educated groups. Therefore, it will certainly be true that the dollar flows are progressive, in the sense that they replace a greater percentage of income for the poorest groups.

We can do a quick "reality check" on these numbers by calculating the associated internal rates of return for each group and comparing them to those predicted by a simple generational accounting framework. Table 7 displays the internal rates of return. At historical rates of

Medicare benefit growth, around 4%, the overall rate of return is between 5.1% and 5.2%. We can compare this to a simple calculation of the rate of return from an overlapping generations model. Suppose cohorts live for two periods: during the first period, they work and pay Medicare taxes, and during the second they receive Medicare benefits. Define n_t as the size of the cohort that is working at time t, define B_t as the Medicare benefits paid at time t and τ_t as the taxes paid at time t. Assuming that Medicare is a strictly pay-as-you-go system, we would have the balanced budget constraint:

$$n_t \tau_t = B_t n_{t-1} \tag{6.1}$$

The rate of return earned on Medicare by the time t cohort is:

$$1 + r_{t-1} = \frac{B_t}{\tau_{t-1}} = (1 + \beta_{t-1})(1 + \pi_{t-1}), \tag{6.2}$$

where β_{t-1} represents the rate of growth in benefits from time $t-1$ to time t, and π_{t-1} represents the rate of growth in population over the same period. Taking logarithms yields the approximation:

$$r_{t-1} \approx \beta_{t-1} + \pi_{t-1} \tag{6.3}$$

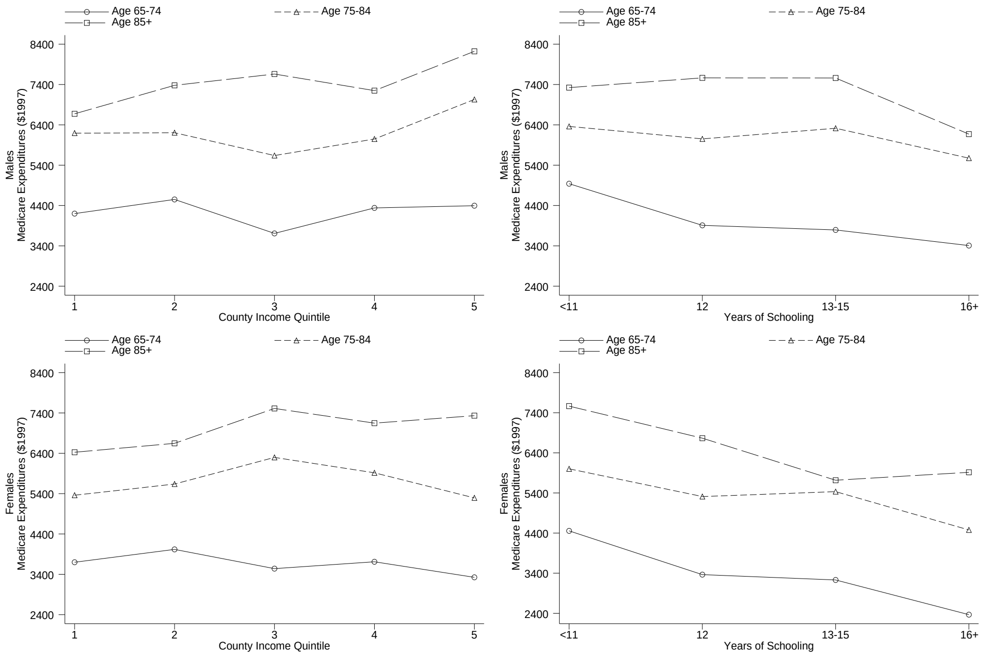
Thus, the return on Medicare is approximately equal to growth in per capita benefits plus population growth. From 1966 to 2000, the rate of growth in the 18-65 year-old population was approximately 1.4% annually, while the rate of growth in real per capita Medicare benefits was about 4 percent annually. This roughly corresponds to a 5.4 percent annual return on Medicare. This back of the envelope calculation is in the same ballpark as our estimated internal rates of return.

7 Aggregation Bias

Unlike McClellan and Skinner (1997), we find that the financial returns to Medicare are much higher for disadvantaged groups, both in absolute terms and *a fortiori* as a percentage of lifetime income. The key source of difference in our results is the finding that Medicare benefits are significantly higher for less educated groups. Other research using aggregate measures of SES find a flat or positive SES gradient in benefits. Aggregate measures of SES may understate the progressivity of Medicare by enough that it can dramatically affect conclusions about redistribution. Using aggregate measures of SES, McClellan and Skinner (1997) find that Medicare transferred dollars from the poor to the rich, but as we have shown, the use of individual-level measures of SES leads to very different conclusions. To be more confident about this claim, however, we must rule out some alternative sources of differences between our results and those of previous researchers. The most obvious difference is in our use of the MCBS, while other researchers have tended to use linked Medicare Administrative Claims data. However, if the difference in data sets is not important, we ought to see that the use of neighborhood income data in the MCBS itself also has the effect of flattening the negative SES gradient.

Since the MCBS reports the county of residence for each respondent, we link the MCBS to BEA data on per capita income (described in Appendix A) at the county level for each year of the survey. We then split up the MCBS sample into county income quintiles, using the MCBS sample weights. In essence, we are ranking each year's MCBS respondents by county income, and then dividing up each yearly ranked sample into five quintiles of equal

Figure 3: Per Capita Medicare Benefits Across Education Groups and County Income Quintiles.



population weight.

Figure 3 reports the results. The left-hand panels depict the benefit gradient across county income quintiles, while the right-hand panels depict the gradient across education groups. The data points in the right-hand panel correspond to the figures reported in Table 2. The gradient across county income quintiles is either flat or somewhat positive, even though in the same data, the least educated individuals receive the most per capita Medicare benefits.

Aggregation seems to affect the size of the gradient, but not *changes* in the size of the gradient, at least qualitatively. For instance, even across county income quintiles, the gradient for females is more negative than for males. This pattern is replicated across individual education groups as well. Nonetheless, there is a fairly consistent positive trend in benefits across county income quintiles for males 75 and above, and for females over 85. Trends for men aged 65-74 and women aged 65-84 are flat, from the bottom to top quintiles. On the basis of the county income quintile data, we might conclude that residents of richer counties spend more or about the same amount of Medicare's resources, but the individual-level data suggests that the most educated people use by far the least amount of resources.

Aggregate measures of education seem to produce results similar to those of aggregate income. Data from the 1990 Census data (described in Appendix A) allow us to compute the fraction of people within each county who had at least a college degree (the average proportion is about 20%) in 1989. Based on the fraction of College Graduates, we construct county education quintiles.[13] The results are shown in Figure 4.

The difference between Figures 3 and 4 is at the top quintiles. For the education measure, there is a decline between the fourth and five quintiles that was not observed with the income measure. The overall slope of the education curves, however, is either somewhat increasing or flat, similar to the county income curves.

Previous research using aggregate measures of income (e.g., McClellan and Skinner, 1997) used income measured at the level of the zip code, rather than the county. Using the MCBS Zip Code data, we link the MCBS to measures of per capita income in each Zip Code from the 1990 Census, which reports 1989 income.[14] Figure 5 reports the results of computing Medicare benefits across Zip Code income quintiles.

The curves across Zip Code quintiles are flat or slightly increasing for men and women over age 75, but they do decrease for people aged 65-74. In fact, they show significant negative

[13]One caveat to note is that we link the 1989 Census Data to the 1992-8 MCBS data and thus could be measuring county education with error. This could flatten the slope of the resulting curves.

[14]The Census data are described in Appendix A.

Figure 4: Per Capita Medicare Benefits Across Education Groups and County Education Quintiles.

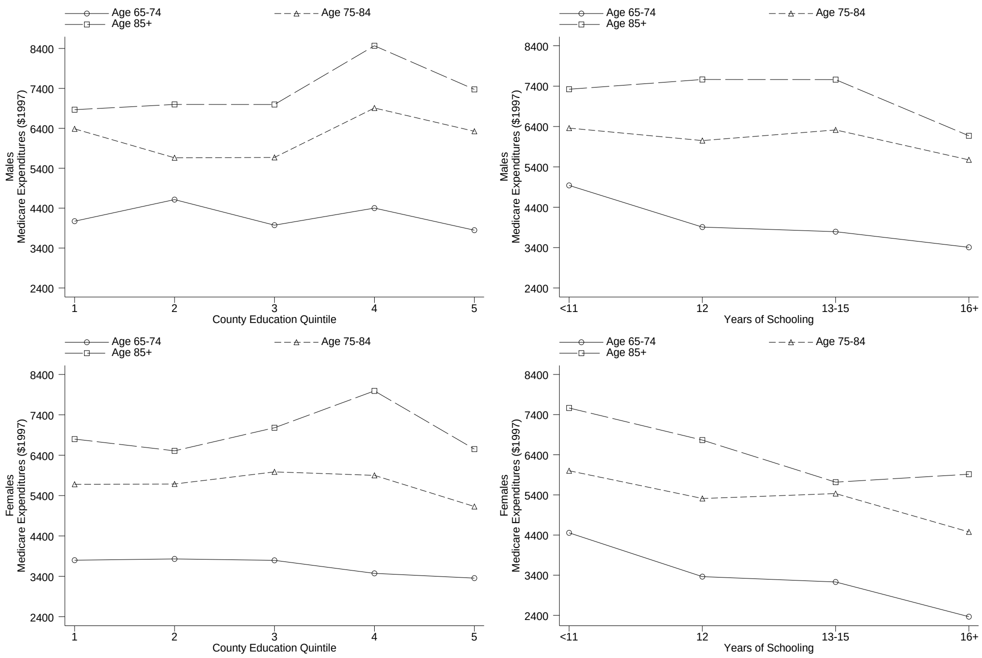
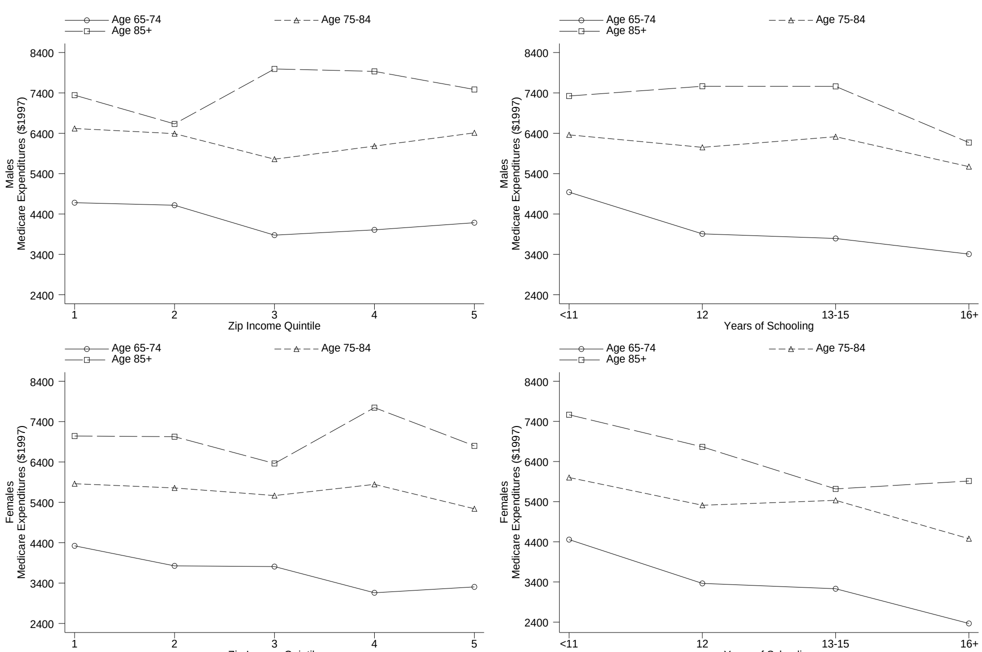


Figure 5: Per Capita Medicare Benefits Across Education Groups and Zip Code Income Quintiles.



gradients for this age group. However, the magnitudes are still not close to the magnitudes for the individual-level data. From peak-to-trough, the zip income quintile declines by $1000 for females and $700 for males. In contrast, the gap between high school dropouts and college graduates is $2000 for females and $1500 for males, about twice as large. Assuming we can trust the measurement of zip code income data, it would appear that using this lower level of aggregation does lessen the discrepancy with the individual-level measures, although only partially.

At the county-level, aggregate measures of SES do not produce negative gradients, whether SES is measured using education or income. At the zip code-level, it is possible to produce negative gradients using income data, but these are consistently (indeed, in every case) half the size of the corresponding gradients using individual-level data. It seems that aggregate measures of SES understate the benefits of Medicare to the poor.

8 Conclusions

At any given age, the poor seem to receive more real Medicare benefits than the rich, at least when poverty is measured using individual-level educational attainment. These gradients are significant enough that they almost exactly offset the effects of early mortality for the poor. As a result of these gradients, it appears that Medicare transfers considerably more resources to the poor than previously thought. In addition, it also appears that measuring SES using aggregated income measures may understate the true benefits of Medicare to the poorest groups.

Compared to previous work, our results are much stronger in favor of the conclusion that Medicare benefits the poor. They would only be strengthened if we also accounted for the observation of McClellan and Skinner (1997) that the nonpecuniary value of Medicare is higher for the poor than for the rich. Not only is Medicare progressive in the sense that its value represents a larger percentage of lifetime income for the poor, but the net present value of Medicare is actually higher in absolute terms for high school dropouts than for college graduates.

While we have investigated the financial returns to Medicare, further research is needed to determine the true welfare consequences of Medicare, which include more than just the pure dollar transfers. A dollar of Medicare benefits may have different values for people in different educational groups, primarily because the alternatives to Medicare may involve very different welfare levels for each educational group. For example, Medicare is much more valuable to a group that would have had no insurance in its absence, and much less valuable to a group that would have preferred to consume less insurance than Medicare mandates were it given the choice.

APPENDIX

A MCBS data

The MCBS contains detailed data on health expenditures and especially on Medicare expenditures. MCBS respondents are linked to Medicare administrative data on claims.[15] From the claims data, the MCBS constructs total annual Medicare fee-for-service expenditure for each respondent, as well as the total annual payment made to a Medicare HMO on behalf of each respondent.[16] The sum of the two represents Medicare's total outlay on each individual.

Medicare fee-for-service payments can be further broken down into Part A and B expenditures, by using data on the type of service rendered. MCBS breaks expenditures down into the following service categories: inpatient hospital visits, outpatient hospital visits, institutional utilization stays, facility stays, home health utilization, hospice stays, medical provider visits, prescribed medicine, and dental visits. We take Part A expenditures to be Medicare fee-for-service expenditures for: facility visits, home health utilization, hospice visits, inpatient hospital visits, and institutional utilization. Part B expenditures are Medicare fee-for-service expenditures for: dental visits, medical provider fees, and outpatient hospital visits.

The geographic identifiers in the MCBS allow us to link it to several important databases discussed in the text. The first is a data set containing the GPCI used to deflate Medicare physician payments across counties, and the hospital wage-price index used to deflate hospital payments across counties. These are used by Medicare to convert expenditures in each county

[15]For details of the linking procedure, see Eppig and Chulis (1997).

[16]About ten to fifteen percent of elderly Medicare beneficiaries are enrolled in Medicare HMOs. These are private HMOs that contract with Medicare to provide medical care in exchange for a flat, per capita fee.

to "relative value units" that are comparable across locales. They are available by county and year. We deflate Part A expenditures using the hospital wage-price index and deflate Part B expenditures and HMO capitation payments by the GPCI deflators. The second data set contains Bureau of Economic Analysis data on per capita personal income at the county and state level, available by year. Of course, since the BEA classifies counties according to the FIPS scheme, and the MCBS classifies them according to the SSA scheme, a crosswalk is used. The last is data from the 1990 Census on 1989 per capita income and area-wide educational attainment at the zip code, county, and state levels.[17] The data contain the number of residents in each zip code, county, and state with a certain educational attainment, along with the total residents. They also contain per capita income data at each level of geographic aggregation. Using these three databases, we are able to augment the MCBS data so that it contains for each respondent: county-level price deflators for all components of Medicare; per capita personal income in state of residence for each year; per capita personal income in county of residence for each year; per capita income in zip code of residence during 1990; and educational attainment in the state, county, and zip code of residence during 1990.

B Health and Retirement Study

The HRS is a longitudinal study of individuals born between 1931 and 1941, who have survived until 1992. The first wave of the HRS was conducted in 1991. The fifth wave collected data for 1999. It can be linked to quarterly Social Security Administration (SSA) earnings records that go back to 1951. This linked file contains earnings records for 9537 HRS respondents present in Wave 1. Between the linked file and the HRS main files, we

[17]These data are taken from GeoLytics (1996).

have quarterly earnings histories from 1951 through 1999. The linked Social Security file contains data on Social Security covered earnings, or the amount of earnings subjected to Social Security payroll taxes. However, from 1966 to 1992, the Medicare earnings maximum was the same as the Social Security earnings maximum.

B.1 Interpolation Across Time in the HRS Main File

We use five waves of the HRS data. Waves 1 and 2 record income data from 1991 and 1993, respectively. Wave 3 records it in 1995 or 1996, depending on when the interview was conducted. Wave 4 records it in 1997 or 1998, and Wave 5 records 1999 data. From these data, we exponentially interpolate missing years, but only if we have data on years prior to *and* following the missing year. In other words, we do not extrapolate any data.

B.2 Family Tax Liability

Since Medicare is financed by a payroll tax, the total expected tax liability ought to be calculated at the level of the family. Men tend to work more and pay more taxes than women, but these are taxes borne by the entire family, rather than just the individual man. The HRS data simplifies the task of computing annual taxes paid by couples, since a reasonable number of married couples in the HRS cohort are both present in the HRS data and the linked Social Security earnings data. For these people, we have complete data on the couple's income. The remaining respondents include the never married, widow(er)s, divorce(e)s, and married people whose spouse is simply not present in the linked earnings file. For these people, we must impute spousal earnings, according to an algorithm we describe below.

Table 8: Availability of data in the HRS Earnings History File.

Marital Status in 1991	Presence in Earnings History File: Respondent and Spouse Present	Respondent Only Present	Respondent Not Present	Total
Married, Spouse Present	6427	975	2435	9837
Married, Spouse Absent	12	22	23	57
Partnered	229	54	102	385
Separated	0	222	88	310
Divorced	0	807	270	1077
Widowed	0	457	163	620
Never Married	0	264	98	362
Unknown	0	68	762	830
Total	6668	2869	3941	13478

Table 8 provides a useful description of the data. There are 13,478 respondents in Wave 1 of the HRS. 3941 of these are not present in the linked Earnings History file. We drop these observations. As long as selection into the Earnings History file is random, this introduces no bias.[18] Another 6668 people (or 3334 couples) are present with their spouses or partners in the Earnings History file. For each of these people, we are able to calculate earnings for the couple. Of the remaining 2869 people, 264 were never married; as such, individual income is equal to family income, and we drop the 68 respondents for whom marital status is unknown. This leaves 2537 people for whom family income must be imputed. Consider first the 1051 married or partnered respondents in this group. We impute spousal earnings by looking at similar respondents and calculating the earnings of their spouses. Specifically, we compute the real average spousal earnings profile of all similarly aged and educated HRS respondents (of the same sex). The average earnings profile is then assigned to each respondent whose spouse is not present in the data. As discussed above, the 1029 divorced or separated respondents are treated as if they were married; average spousal earnings are

[18] Haider and Solon (2000) show that, conditional on having a Social Security Number, selection into the SSA file is indeed random.

imputed for them according to the same procedure. Even if the individual has been divorced more than once, our strategy will not be affected, as long as his spouses have been similarly educated.

This leaves only the 457 widowed respondents. The difficulty with these respondents is estimating the year of their spouse's death, which is not reported in the data. The best we can do is to make use of the HRS variable for "length of longest marriage." For those who are currently married in wave one of the HRS, we compute the year they would have been married, assuming that their current marriage is their longest marriage. This yields the most recent year in which they could have been first married. We then compute the average year within the four education groups we are considering, racial category (white, black, or other), and age in 1991. This yields our estimate of year of marriage for widow(er)s. Using the variable for length of longest marriage, we then compute the year in which each widow's spouse would have died. This date is used to truncate the average real spousal earnings profile estimated above, and this finally yields the earnings that the deceased spouse would have contributed to the partnership. As a result of the data limitations we face, this is a highly imperfect strategy, but it is important to stress that it affects less than 5% of our sample. Even if we were to mismeasure income by 50% for these respondents, it would have less than a 3% impact on our estimates of average income.

B.3 Self-Employment Income

The HRS SSA file does not break apart taxable income into self-employment income and wage income, even though Medicare taxed these two types of income at different rates from 1966 to 1983. Today, the worker and firm each pays half the tax on wage earnings. However, through 1983, self-employed people paid at the tax rate faced by the worker alone, which amounts to half the total Medicare tax paid. Prior to this year, therefore, self-employed individuals faced a lower total tax rate than workers. During the years with a Medicare earnings cap, if a worker had earnings both from wage work and self-employment, her wage taxes were calculated first, and then her self-employment tax. For example, suppose a worker in 1967 had $6000 in wage income, and $4000 in self-employment income. Taxes would have been collected on all her wage income, but only the first $600 of her self-employment income. Her total tax would have been: (1.0%)*$6000+(0.5%)*$600=$63.

To decompose the HRS income measures into self-employment income and wage income, we use data from the 1966-83 Current Population Surveys (CPS). The CPS asks respondents about wage income, self-employment income, age, sex, educational attainment, and race. From the CPS, we estimate-for every survey year, 5-year age group, education group, sex, and race-the average proportion of total income subject to Medicare tax that was derived from self-employment. We restrict these calculations to CPS respondents that reported some income during the year. These proportions are then used to impute self-employment income and wage income for the 1966-83 period. In practice, these imputations had very little effect on our estimated rates of return from Medicare. Even ignoring this issue—and treating all 1966-83 income as wage income—yields virtually the same rates of return. Nonetheless, for the sake of consistency, we estimate self-employment income. Table 9 displays these estimated proportions for the age ranges occupied by the HRS cohort in 1966 and 1982. Self-employment income is relatively for women and young men throughout these age ranges. It is, however, somewhat important for men over the age of 40, and particularly for high school graduates.

Table 9: Proportion of Self-Employment income in the HRS Cohort.

	Age Group	Males: Less than HS	Males: HS Graduate	Males: Coll Attendee	Males: Coll Grad	Females: Less than HS	Females: HS Graduate	Females: Coll Attendee	Females: Coll Grad
1966	25-29	1.3%	2.6%	3.0%	2.1%	1.4%	1.8%	8.5%	2.1%
	30-34	2.2%	4.8%	2.2%	2.9%	1.4%	1.9%	7.8%	0.8%
	35-39	3.7%	7.0%	7.0%	6.6%	3.6%	3.9%	2.8%	2.1%
1982	40-44	4.8%	6.0%	5.3%	8.8%	5.1%	4.6%	6.3%	2.1%
	45-49	6.9%	12.6%	11.5%	9.1%	8.7%	4.3%	3.8%	9.9%
	50-54	8.4%	9.1%	8.4%	16.1%	4.0%	3.2%	3.7%	5.7%

Source: Current Population Surveys, 1966-82.

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