Does Medicare Benefit the Poor?*

Jay Bhattacharya†
Stanford University and NBER

Darius Lakdawalla‡
RAND Corporation and NBER

January 5, 2005

Abstract

Measuring the progressivity of age-targeted government programs is difficult because no single data set measures income and benefit use throughout life. Previous research, using zip code as a proxy for lifetime income, has found that Medicare benefits flow primarily to the most economically advantaged groups, and that the financial returns to Medicare are often higher for the rich than the poor. However, our analysis produces the starkly opposed result that Medicare is an extraordinarily progressive public program, in dollar terms or welfare terms. These new results owe themselves to our measurement of socioeconomic status as an individual's education, rather than the geographically aggregated measures of income used by previous research. We argue that individual education has important practical and conceptual advantages over geographically aggregated measures of income. Our results suggest the crucial importance of accurate poverty measurement in evaluating the progressivity of complex government programs like Medicare or Social Security.

*We are grateful to an editor of the *Journal*, two anonymous referees, as well as Henry Aaron, Amitabh Chandra, David Cutler, Mark Duggan, Bill Evans, Victor Fuchs, Alan Garber, Dana Goldman, Stan Panis, Seth Sanders, Michael Schoenbaum, and seminar participants at the University of California-Irvine, University of Maryland, Stanford Medical School, the Spring 2002 NBER Health Care Program Meeting, the 2003 American Economic Association Meetings, and the 2003 NBER Summer Institute for numerous helpful comments and suggestions. We are especially grateful to Jonathan Skinner for many valuable discussions and suggestions. Melinda Beeuwkes Buntin kindly shared her data and insights on Medicare price deflators and Medicare HMO payment schedules. The authors are grateful for National Institute on Aging Grants R03 AG20266-01 and R01 AG021940.

†Stanford University, Center for Primary Care and Outcomes Research, 117 Encina Commons, Stanford, CA 94305-6019. jay@stanford.edu

‡RAND Corporation, 1700 Main Street, Santa Monica, CA 90407. darius@rand.org

1 Introduction

Many people would believe a government program to be unjust if it transferred resources from the poor to the rich. It is thus a bit troubling that previous research finds Medicare to be functioning in exactly this way,[1] even though it is typically seen as one of the most important layers in the social safety net for the poor elderly. The previous literature finds that the poor use fewer Medicare resources at any given age, and that their earlier mortality further deprives them of Medicare benefits.[2] This is found to offset the advantages in expected tax payments they enjoy.

The distributional impacts of Medicare are difficult to assess, because they are obscured by Medicare's intricate lifetime financing mechanism. The results of any analysis thus depend crucially on the accurate measurement of *lifetime* poverty. The most widely accepted and feasible measures of poverty—such as position in the income or wealth distribution—tend to be static in nature, and are not suitable for measuring the progressivity of lifetime programs. In response, many researchers use neighborhood-level income measures as a proxy for lifetime socioeconomic status. These analyses tend to produce the result that Medicare benefit levels are higher in richer neighborhoods, and that Medicare either transfers lifetime financial resources from the poor to the rich, or at a minimum does not transfer resources to the poor.

Our analysis takes a different approach to poverty measurement, and produces a strikingly different result: at any given age, Medicare spends far more on the poor than the rich. As a result, Medicare is actuarially unfair or neutral for college graduates, while high school

[1] See Long and Settle (1984), or Gornick et al. (1996). Based on more recent Medicare benefit data, McClellan and Skinner (2003) find rough neutrality in dollar flows, while for 1987 data they find resources flowing from poor to rich.

[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. Panis and Lillard (1996) find that accounting for finer differences in mortality rates compresses progressivity further.

dropouts almost double their money. Moreover, as McClellan and Skinner (2003) show, the pure financial returns likely understate the overall progressivity of the program.

Unlike previous researchers, we use an individual's own educational attainment as a measure of socioeconomic status, rather than neighborhood income. Less educated individuals consume far more Medicare benefits than the more educated even though individuals who live in richer or more educated *areas* receive more benefits. Moreover, we show that 75 and 85 year-olds immediately increase their medical spending when they move to richer areas, and vice-versa for moves to poorer areas. This suggests that area of residence picks up health expenditure variation that is unrelated to an individual's permanent income, which is unlikely to change at age 75 or 85. Education also has important conceptual advantages over neighborhood income, because it measures socioeconomic status before the effects of old-age transfer programs register on realized lifetime income.

2 A Framework for Measuring Progressivity

2.1 Measuring Socioeconomic Status

To measure the lifetime progressivity of a public program requires a definition of socioeconomic status, which we take to mean permanent income. Since this is unobserved, a proxy must be used. Average income in an individual's zip code or area of residence serves as a proxy because it smooths out life-cycle and idiosyncratic fluctuations in income, but it introduces the possibility of aggregation bias (Geronimus et al., 1996). Richer areas may have higher quality medical facilities.[3] Such areas might thus provide more care to a fixed individual, or might draw in sicker people. In either event, area income would generate a more positive gradient in medical expenditures than an individual's actual socioeconomic status.

[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.

Several previous studies have found higher Medicare expenditures in wealthier areas,[4] but is this really because wealthier *people* cost Medicare more?

One way to assess this is to measure socioeconomic status at the individual level. While an individual's current-period income is subject to idiosyncratic and life-cycle fluctuation, a more theoretically sound measure of socioeconomic status is an individual's educational attainment.[5] Permanent income is generated by the returns to human and nonhuman capital. Though human capital consists of both schooling and unobserved ability, a great deal of research in labor economics suggests that schooling is a good measure of human capital, and that unobserved ability is not a large component of it (cf, Card, 1995). In addition, the vast majority of aggregate wealth in the economy is human capital (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.

2.2 Measuring the Returns to Medicare

In the Social Security progressivity literature, researchers have reported the returns to the program using two closely related measures. In our case they yield the same answers. The first measure calculates the expected net present value of Medicare for each socioeconomic group, and then divides by the expected net present value of lifetime income. This is analogous to a calculation of income tax incidence, which divides a group's tax bill into its income to arrive at its percent tax incidence. The second measure is the internal rate of return, which yields the rate of return one would have to earn on a lifetime annuity to obtain the

[4]See, for example, Long and Settle (1984). McClellan and Skinner (2003) find a distinctly positive relationship between zip code income and benefits in 1987, a move towards progressivity during the 1990s, and a retrenchment thereafter. Over the entire time period, their estimated relationship ranges from weakly to strongly positive.

[5]In section 7.2, we compare directly how well neighborhood level income measures and education measure lifetime income.

expected net present value of the public program. This is based on the analogy between a lifetime public program and a financial market instrument.[6]

To construct the net present value of 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 risk-free rate of interest is r—commonly estimated at around 3% per annum (Siegel, 1992)—the expected net present value of Medicare transfers to i at age 18 is equal to:

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

Lifetime tax incidence is given by this quantity, divided by lifetime income.

The internal rate of return is obtained by rewriting equation (2.1). In particular, it is the scalar ρ that solves the following equation:

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

In measuring the returns to Medicare, measuring financial returns is only a first step—we need also to know how these financial returns relate to the total impact on individual welfare. McClellan and Skinner (2003) show that the financial returns to Medicare *understate* the relative benefit to the poor, who disproportionately benefit from the increased access to insurance provided by Medicare. Based on this argument, if Medicare's pure financial transfers benefit the poor, its overall transfers of welfare are likely to benefit the poor also.

[6] Further discussion of these issues can be found in the literature on the returns to Social Security (cf, Hurd and Shoven, 1985; Duggan et al., 1993; Garrett, 1995).

3 Mortality and Socioeconomic Status

The first element of our calculation is a life table for the 1931-41 birth cohort by sex and education. For ages over 65, we use the 1992-99 Medicare Current Beneficiary Surveys (MCBS) to estimate age-, sex-, and education-specific death rates directly.[7] For those under 65, we start with the 1931-41 birth cohort life table from the Human Mortality Database (www.mortality.org).[8] This yields $\hat{S}_t$, the average probability of survival to age t. Using the 1993 National Mortality Followback Survey (NMFS), we estimate for each education group i, $\frac{S_{it}}{\hat{S}_t}$—the group-specific survival probability to age t as a fraction of the average probability—by sex and age group. The group-specific life tables are obtained by calculating $\hat{S}_t * \frac{S_{it}}{\hat{S}_t}$, which equals S_{it}, our object of interest. Further details appear in Appendix A.

Figure 1 graphs the resulting survival curves for men; corresponding curves for women appear in Appendix A. 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). High School dropout males in this cohort are twenty-one percentage points less likely to survive to age 65, while females are only about twelve percentage points less likely.

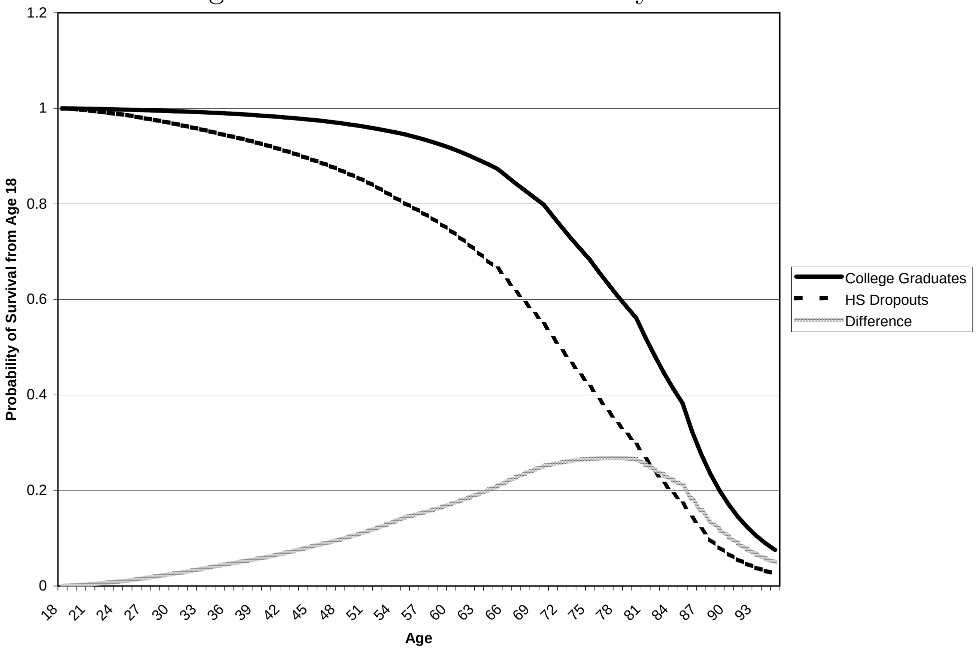
4 The Distribution of Medicare Benefits

We calculate age-specific Medicare benefits, B_{it} using the MCBS Cost and Use Files. These are nationally representative and longitudinal datasets designed to ascertain expenditures for the Medicare population. They are currently available every year from 1992 to 1999. The sample is randomly drawn from all aged and disabled Medicare enrollees, and information on Medicare Parts A and B is available. The oldest-old—85 years of age or over—are

[7]Average MCBS death rates match *Vital Statistics* death rates almost exactly.

[8]This yields life tables for each single-year birth cohort. The 1931-41 cohort life table is constructed by averaging over them.

Figure 1: Male Survival Curves by Education.



oversampled. In addition to health, the MCBS contains data such as age, sex, race, and educational attainment, along with state, county, and zip code of residence.

4.1 Age-specific Medicare Expenditures

Table 1 presents average real (1997 dollars) per capita Medicare benefits by age group, sex, and educational attainment for 77,581 elderly Medicare enrollees.[9] The top panel of the table shows the educational gradient in total Medicare benefits. These benefits consist of Medicare Parts A and B fee-for-service expenses, plus payments made by Medicare on behalf of its beneficiaries to Medicare HMO's.[10]

In these data, there are consistent negative gradients in education (that is, low SES

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

[10] We exclude medical expenditures paid by the HMO's themselves since including these would represent double-counting. The actual payment made by Medicare to the HMO represents the full 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, or the return on taxes paid into Medicare.

Table 1: Real Per Capita Medicare Benefits by Educational Attainment.

		Males				Females			
		High Sch Dropouts	High Sch Grads	College Attendees	College Grads	High Sch Dropouts	High Sch Grads	College Attendees	College Grads
Total Medicare	65-74	$4,367	$3,416	$3,336	$2,982	$4,021	$2,925	$2,810	$1,915
	75-84	$5,732	$5,530	$5,741	$5,252	$5,461	$4,838	$4,784	$3,822
	85+	$6,799	$7,401	$6,854	$6,597	$7,049	$6,617	$5,208	$5,430
Medicare Part A	65-74	$2,817	$2,004	$1,844	$1,704	$2,448	$1,732	$1,602	$909
	75-84	$3,516	$3,458	$3,297	$3,056	$3,553	$3,008	$2,965	$2,218
	85+	$4,646	$5,242	$4,753	$4,315	$4,935	$4,663	$3,381	$3,869
Medicare Part B	65-74	$1,018	$832	$756	$774	$1,152	$684	$615	$570
	75-84	$1,399	$1,291	$1,571	$1,589	$1,384	$1,136	$1,112	$1,000
	85+	$1,343	$1,360	$1,250	$1,500	$1,484	$1,296	$1,080	$1,103
Medicare HMO	65-74	$532	$580	$736	$504	$421	$509	$593	$436
	75-84	$818	$781	$872	$607	$524	$694	$708	$604
	85+	$809	$799	$851	$782	$630	$659	$746	$458

Source: MCBS, 1992-1999.
Notes: All values are per capita real 1997 dollars. N=77,581: detailed sample sizes by cell are in Appendix B.

individuals spend 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 men) 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.

Most of the negative gradient is driven by variation in Part A, or hospital insurance benefits, but there is a consistent negative gradient in Part B benefits. It is not as large in magnitude, but we show in Appendix B that it is likely to be enough to yield progressivity for Part B also. For Medicare HMO payments, while the patterns are not so clear, the best characterization is a slight positive gradient, perhaps because Medicare HMOs tend mainly to be available in richer, urbanized areas of the country.

Part, though not all, of the negative gradient is explained by differences in observed 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.[11]

[11]The rest could be generated by variation in unobserved health, but it could also be related to differences

4.2 Lifetime Medicare Benefits

Differential mortality erodes the advantage of the poor and makes the absolute benefit gradient slope upwards in education from age 75 (see Appendix B). To assess the overall impact of this, we use the data in Table 1, along with the estimated survival profiles, to construct the expected present value of lifetime Part A benefits from the point of view of an 18 year-old in the 1931-41 birth cohort.[12] While Appendix B gives the details of this calculation, Table 2 documents the results for various real interest rates and two real benefit growth rates.[13]

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 9% fewer lifetime benefits than college graduates at a 3% real rate of interest and 4% real rate of benefit growth. Female high school dropouts actually receive more benefits than college graduates, even in expected present value.

5 The Lifetime Incidence of Medicare Taxation

The last step in estimating the expected net present value of Medicare is the construction of 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 payroll tax liability of the 1931-1941 birth cohort.[14] This includes both individual tax payments and payments by employers, which are assumed to be ultimately

in public and private insurance coverage, or other factors. Not surprisingly, there is a positive gradient in privately financed medical expenditures, once one controls for health.

[12]This includes payments made in both fee-for-service and HMO arrangements. Appendix B explains how we decompose both types of payments into Part A and B components.

[13]Lifetime benefits are once again shown in constant 1997 dollars.

[14]Since HRS data are not linked to income tax records, we cannot estimate individual contributions to general revenues. We can only directly estimate the progressivity of Part A, funded mainly by payroll taxes, not Part B, which is funded by premia and general revenues. In Appendix B.5 we show that Part B is also progressive.

Table 2: Expected Present Value of Real Part A Medicare Benefits, by Sex and Education.

	Real Interest Rate	Male				Female			
		High Sch Dropouts	High Sch Grads	College Attendees	College Grads	High Sch Dropouts	High Sch Grads	College Attendees	College Grads
No Growth	0%	$40,181	$41,473	$43,354	$47,057	$55,293	$50,633	$51,901	$42,802
	1%	$23,803	$23,557	$24,435	$26,223	$31,551	$28,156	$28,844	$23,253
	2%	$14,415	$13,616	$13,988	$14,820	$18,400	$15,924	$16,292	$12,812
	3%	$8,945	$8,022	$8,139	$8,498	$10,999	$9,174	$9,362	$7,163
	4%	$5,701	$4,828	$4,820	$4,947	$6,763	$5,396	$5,482	$4,067
	5%	$3,742	$2,978	$2,908	$2,926	$4,297	$3,250	$3,277	$2,348
4% Ann. Growth	0%	$59,415	$67,996	$72,358	$80,765	$91,849	$89,120	$91,442	$80,658
	1%	$34,049	$37,520	$39,648	$43,866	$50,635	$48,142	$49,367	$42,743
	2%	$19,933	$21,045	$22,054	$24,152	$28,471	$26,412	$27,060	$22,951
	3%	$11,947	$12,015	$12,462	$13,486	$16,370	$14,736	$15,072	$12,492
	4%	$7,352	$6,997	$7,160	$7,640	$9,658	$8,376	$8,542	$6,896
	5%	$4,658	$4,167	$4,188	$4,395	$5,873	$4,863	$4,933	$3,865

Note: All figures are in real 1997 dollars, from the point of view of an 18 year-old. Calculations are based on 1992-99 MCBS, and mortality data from NMFS.

borne by workers.[15]

The HRS is a nationally representative longitudinal household dataset with detailed demographic and financial data on respondents. The advantage of the HRS is that it can be linked with the restricted-use Social Security earnings file. Based on Social Security Administration records, the restricted file contains quarterly reports on respondents' earnings that were subject to payroll taxation, for every quarter from 1951-1990. These are entirely from administrative records, rather than retrospective self-reports, and are available for 9537 of the 13,478 people present in Wave 1 of the HRS.[16] Over this period of time, the earnings subjected to Medicare taxation was identical to Social Security earnings. From 1991 to 1999, we have detailed self-reported data on wage and self-employment earnings from the HRS itself. From these two data sources, we construct the payroll tax payments of each individual, from the inception of Medicare until 1999.[17]

[15]This assumption is not crucial. Under the extreme assumption of perfect pass-through for high school dropouts and none for college graduates, Medicare's net present value is at most twenty percent higher for college graduates, far less than the corresponding gradient in lifetime income.

[16]Haider and Solon (2000) show that this seems to be a random subsample of HRS respondents with social security numbers.

[17]Details on the construction of earnings and taxes are presented in Appendix C.

Any calculation of tax liability must account for division of labor and income-sharing within the family. For instance, even though the males in this cohort have higher labor force attachment and higher payroll tax outlays, it would be misleading to allocate all of this to husbands. If market and home work are shared within a family, so too are market wages and market taxes. Since there is no inarguable sharing rule, we show that the choice of sharing rule does not affect our results.

Our first strategy takes the view that couples share their *lifetime* wealth with each other.[18] Since this is a particularly altruistic view of income-sharing, we complement it by repeating the calculation under a particularly individualistic view of income-sharing using the Current Population Survey (see Appendix D). Our results are qualitatively similar.

To implement the life-cycle sharing approach, we need to compute taxes paid at the family level. The HRS eases this task because it includes earnings histories for most couples that were still together at the HRS baseline.[19] Based on historical tax rates, we estimate taxes paid using earnings data from the HRS. All these calculations result in an age-profile of real 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 calculate 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 is quite insensitive to various manipulations of our assumptions, described in Appendix C. Not surprisingly, the vast majority of variation across education groups is generated simply by earnings dif-

[18] We think of couples as a family unit before their actual date of marriage, and after their date of divorce, and suppose that there is an implicit or explicit (that is, alimony) sharing rule after divorce.

[19] Appendix C discusses in detail our procedures for imputing missing values for unobserved spouses.

Table 3: Expected Net Present Value of Medicare Payroll Tax Liability faced by Families of HRS Cohort Members.

Real	Male				Female			
Interest	High Sch	High Sch	College	College	High Sch	High Sch	College	College
Rate	Dropouts	Grads	Attendees	Grads	Dropouts	Grads	Attendees	Grads
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 real 1997 dollars, from the perspective of an 18 year-old in the HRS cohort.

ferences.[20]

6 The Value of Medicare

To arrive at financial returns to Medicare, we have to reconcile the tax liabilities of families, in Table 3 with the expected medical benefits of individuals, in Table 2. In keeping with our life-cycle sharing assumption, we convert the data on individual medical benefits to family benefits by matching men and women. We impute spousal Medicare benefits using age, sex, race, and educational attainment.[21]

After converting Table 2 to a family basis, we compute the expected benefits minus costs of Medicare for the families of people of a specific sex and educational attainment. The net flows are depicted in Table 4. Given a real rate of interest at 2% or higher, they fall uniformly with education. *A fortiori*, therefore, the dollar flows are progressive in the sense of replacing a greater percentage of income for poorer groups. While we lack similarly detailed

[20]The families of women have fewer liabilities for two reasons. The first is the timing of Medicare for this 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. This accounts for about three-quarters of the gap and does not affect our conclusions for progressivity. The second reason is the higher earnings of male workers. For unmarried or widowed individuals, men have higher earnings; this is compounded by the fact that women are more likely to be widowed.

[21]Details of this procedure are contained in Appendix B. In Appendix D, we present sensitivity analyses suggesting that this imputation does not drive our results.

Table 4: Expected Net Present Dollar Flows from Medicare Part A for Families of HRS Cohort Members, by sex and education of the cohort member.

	Real Interest Rate	Male High Sch Dropouts	Male High Sch Grads	Male College Attendees	Male College Grads	Female High Sch Dropouts	Female High Sch Grads	Female College Attendees	Female College Grads
No Growth	0%	$55,190	$49,706	$48,454	$37,659	$53,605	$43,693	$41,923	$27,426
	1%	$28,508	$23,039	$21,697	$13,710	$28,037	$20,233	$18,548	$9,244
	2%	$14,341	$9,559	$8,370	$2,575	$14,428	$8,370	$6,926	$907
	3%	$6,848	$2,897	$1,920	-$2,242	$7,192	$2,505	$1,326	-$2,603
	4%	$2,928	-$252	-$1,027	-$4,004	$3,371	-$266	-$1,207	-$3,797
	5%	$923	-$1,608	-$2,215	-$4,342	$1,385	-$1,457	-$2,202	-$3,926
4% Ann Growth	0%	$98,458	$102,536	$104,612	$99,230	$95,860	$89,965	$90,558	$75,496
	1%	$51,375	$50,785	$51,124	$45,881	$50,249	$44,461	$44,019	$34,273
	2%	$26,559	$24,287	$23,957	$19,564	$26,233	$21,193	$20,413	$14,080
	3%	$13,445	$10,797	$10,265	$6,824	$13,533	$9,365	$8,545	$4,404
	4%	$6,527	$4,029	$3,486	$884	$6,813	$3,442	$2,698	-$30
	5%	$2,906	$735	$251	-$1,681	$3,273	$568	-$68	-$1,881

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

Table 5: Internal rates of return on Medicare Part A by sex, education group, and rates of growth in Medicare benefits.

Ben. Gwth.	Males High Sch Dropouts	Males High Sch Grads	Males College Attendees	Males College Grads	Males Overall	Females High Sch Dropouts	Females High Sch Grads	Females College Attendees	Females College Grads	Females Overall
0%	5.9%	3.9%	3.6%	2.4%	3.4%	6.7%	3.9%	3.4%	2.2%	3.6%
1%	6.2%	4.3%	3.9%	2.9%	3.8%	7.1%	4.2%	3.8%	2.6%	4.0%
2%	6.6%	4.6%	4.3%	3.3%	4.2%	7.4%	4.6%	4.2%	3.1%	4.4%
3%	6.9%	5.0%	4.7%	3.8%	4.5%	7.8%	5.0%	4.6%	3.5%	4.7%
4%	7.2%	5.4%	5.1%	4.3%	4.9%	8.2%	5.3%	5.0%	4.0%	5.1%
5%	7.5%	5.8%	5.5%	4.7%	5.3%	8.5%	5.7%	5.4%	4.4%	5.5%

tax profiles for it, we have shown Part B to be progressive in the sense that net benefits rise more slowly than lifetime income (see Appendix B).

On a family basis, Medicare is more valuable to men than women. This is primarily because men spend a greater proportion of their lives as married; this causes their average family Medicare benefits to be significantly higher, even though they live fewer years than women on average. This effect largely washes out in the internal rate of return calculation, since men pay more taxes. As a result, rates of return are about equal for men and women.[22]

Table 5 displays the internal rates of return associated with these expected net present values. At historical rates of Medicare benefit growth, around 4%, the overall rate of return

[22]The one exception occurs for high school dropouts, where rates of widowhood are highest.

Table 6: Internal rates of return on Medicare Part A for 1931-41 birth cohort at today's tax rates.

	Males					Females				
Ben. Gwth.	High Sch Dropouts	High Sch Grads	College Attendees	College Grads	Overall	High Sch Dropouts	High Sch Grads	College Attendees	College Grads	Overall
0%	2.3%	1.6%	1.6%	1.0%	1.6%	2.7%	1.6%	1.4%	0.8%	1.7%
1%	2.6%	2.0%	2.0%	1.4%	2.0%	3.0%	1.9%	1.8%	1.2%	2.0%
2%	2.9%	2.3%	2.3%	1.9%	2.3%	3.3%	2.2%	2.1%	1.6%	2.4%
3%	3.2%	2.6%	2.7%	2.3%	2.6%	3.5%	2.6%	2.5%	2.0%	2.7%
4%	3.5%	3.0%	3.0%	2.7%	3.0%	3.8%	2.9%	2.8%	2.4%	3.0%
5%	3.8%	3.3%	3.4%	3.1%	3.3%	4.1%	3.2%	3.1%	2.8%	3.3%

is about 5.0%. We perform a quick check on these estimates by comparing them to the rate of return calculated from a simple overlapping generations model. Such a model implies that 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% annually. This back of the envelope calculation roughly corresponds to a 5.4% annual return on Medicare, which is reasonably close to our estimated internal rate of return.

Medicare is likely to be less generous with future cohorts, although it is likely to remain a good deal for the poorest members of those cohorts. Table 6 shows the internal rates of return on Medicare that the 1931-41 birth cohort would have enjoyed if they had paid Medicare taxes at today's rates, from 1951 onwards. The table demonstrates that rates of return would have fallen considerably. At historical rates of benefit growth, Medicare would be actuarially fair for the average person (under the assumption of a 3% real rate of interest), more than fair for high school dropouts, and unfair for college graduates. Under this counterfactual tax structure, Medicare would redistribute from rich to poor in absolute terms.

7 Comparison with Previous Research

Unlike McClellan and Skinner (2003), we find that the financial returns to Medicare are significantly higher for the poor, both in absolute terms and as a percentage of lifetime income. Even their calculations based on data from the 1990s, which more closely approximates our time period, suggest that financial flows are neutral or weakly progressive. Our different conclusions likely owe themselves to our use of an individual-level measure of socioeconomic status, rather than a geographic one: we show that, even in our data, geographic measures of poverty imply much less progressivity for Medicare. We go on to argue that education has several distinct advantages in the analysis of Medicare incidence.

7.1 The Importance of Aggregation

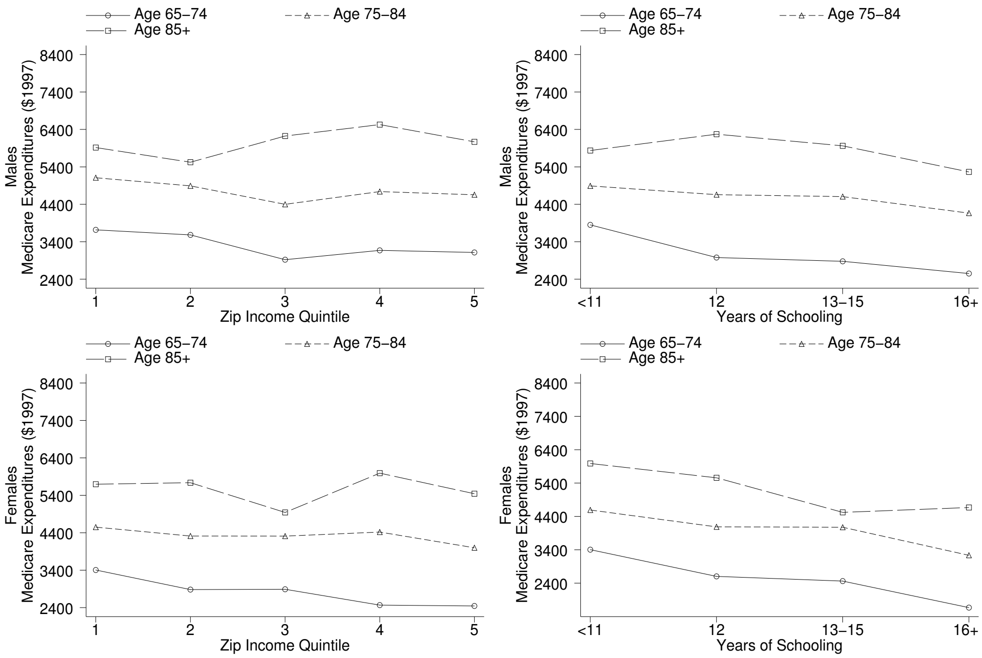
Gradients across zip code income in our data are similar to those in the McClellan and Skinner data. This suggests the importance of the measure, rather than the data set.

Using the MCBS data on zip code of residence, we link the MCBS to measures of per capita income in each zip code from the 1990 Census.[23] Figure 2 shows that, across zip code income quintiles, Medicare expenditures are flat or slightly increasing for men and women over age 75, even though they are strongly decreasing across education levels at these ages. While expenditures decrease across zip quintile for people aged 65-74, the magnitudes are much smaller. From peak-to-trough, the zip income quintile declines by $1000 for females and $700 for males. The corresponding gaps between high school dropouts and college graduates are $2000 for females and $1500 for males.

Other evidence also suggests the importance of aggregation. Greater aggregation results in a more positively sloped income-expenditure relationship: the curve across county income quintiles is more positively sloped than across zip code quintile (see Appendix E). In addi-

[23]The Census data, which report 1989 income, are described in Appendix B.

Figure 2: Per Capita Medicare Benefits Across Education Groups and Zip Code Income Quintiles.



tion, the expenditure curve is similar across county education quintiles and county income quintiles. This suggests that aggregation is the key issue, not education itself.

7.2 Bias in Geographic Measures of SES

A proxy for permanent income is biased if it is correlated with some element of medical expenditures that is independent of permanent income. Zip code income is biased in exactly this sense, because movement to richer areas is correlated with increases in medical expenditure even when permanent income is arguably unaffected.

In the MCBS, elderly migrants to richer areas end up raising their total medical expenditures, while migrants to poorer areas lower them. This could be because people who anticipate falling ill choose to move to richer areas, where medical care is better or more satisfactory to patients. Alternatively, people in richer areas may consume more medical care because standards of care are more intensive. In either event, medical expenditures are

Table 7: Migration and Total Medical Spending Among the Elderly.

	Males		Females	
	65-74	75+	65-74	75+
Summary of Migration				
Proportion Migrating	0.060	0.081	0.071	0.097
Proportion Migrating to Poorer Zip	0.030	0.042	0.036	0.049
Within-Individual Regression on Real Total Medical Expenditures				
1990 Zip Code Income	-0.08	0.32 *	0.05	0.28 *
	(0.14)	(0.12)	(0.08)	(0.07)
Year Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.01	0.02	0.01	0.02
Observations	15033	15369	18022	27880

Notes: Based on 1992-99 MCBS Data. Standard errors appear in parentheses.
*Significant at 1% level.

higher for residents of richer areas for reasons other than their own permanent income.

Table 7 shows the proportion of elderly people in the MCBS switching zip codes and moving to poorer zip codes. The table also shows the results of a within-individual regression of total real medical expenditures on average zip code income as reported in the 1990 Census, and year fixed-effects. The coefficient on zip code income represents the average change in total medical expenditures that accompanies migration to a zip code with \$1 of additional per capita income in 1990. There seems to be no link between migration and spending for the 65-74 year-olds, but for all elderly groups over age 75, a \$1 reduction in zip code per capita income is associated with a statistically significant 28 cent decline in total medical spending. Since these are within-individual estimates, and especially since the effects are confined to the oldest age groups, migration to a poorer area is very unlikely to reflect a decrease in permanent income, but it still seems correlated with a decline in medical spending.

Longitudinal comparisons between migrants to richer and poorer areas also reveal evidence consistent with our interpretations. Before migration, total medical spending is statistically indistinguishable for the two groups, but in the period immediately after migration and two periods after migration, migrants to richer areas spend \$2000 and \$2800 more on annual medical expenditures, respectively (see Appendix E). In addition, observably similar people spend more in richer zip codes than poorer ones: Medicare expenditures rise with zip code income quintile, even controlling for education, age, sex, and year (see Appendix E).

7.3 Conceptual Issues in the Incidence of Medicare

Education has a conceptual advantage as a poverty measure, because it is an ex ante measure of socioeconomic status at labor force entrance, while region of residence is an ex post measure of realized socioeconomic status in old-age. Since public programs seek to influence the ex post distribution of resources, it is inappropriate to evaluate their incidence across ex post categories. If Medicare provides relatively more insurance to the poor, it compresses the income distribution; this is a key effect of the program, but becomes invisible if we examine transfers across the socioeconomic categories existing in old-age.[24]

Moreover, education is a better representation of an individual's socioeconomic status. Unlike region of residence, education intrinsically confers wealth on the individual who possesses it. Therefore, even if it incorporates some health-related factor that is independent of permanent income, this need not generate bias. As an example, consider the hypothesis that educated people sit atop a social hierarchy and enjoy better health as a result (cf Marmot, 2001). In this example, their social position—though possibly independent of permanent income—may legitimately be included as part of their socioeconomic status. More generally, it is hard to imagine characteristics associated with education but not part of socioeconomic status. It is equally hard to document concretely health-related bias in education. An association between education and health expenditures—even controlling for some measure of permanent income—could simply reflect mismeasurement of permanent income.

[24]This could also work in reverse. Since Medicare taxes are directly tied to earnings, the tax gradient across the realized income distribution is about twice as steep as across the education distribution (see Appendix C).

8 Conclusions

Evaluating the economic impact of old-age entitlement programs like Medicare raises difficult but crucial questions of permanent-income measurement. Even well-correlated measures, like individual-level education and neighborhood of residence, can yield quite different results. Our results suggest that Medicare is financially progressive, by a large margin, when permanent-income is measured using individual education. This is in contrast to earlier research using neighborhood-level income, which yields financial neutrality or even regressivity.

The choice of a permanent income measure is both an empirical and a conceptual issue. The empirical question is whether or not the proxy measure is correlated with individual welfare in a way that is unrelated to socioeconomic status. In our case, neighborhood income absorbs area-specific variation in medical care expenses that does not depend on a resident's own permanent income, even though it might depend on his neighbors' incomes. Conceptually, one has to decide when in the life-cycle it is most appropriate to measure socioeconomic status. In the case of Medicare, it seems better to measure the status at which an individual enters adulthood, rather than the terminal old-age status that might already incorporate the effect of transfer programs like Social Security and Medicare.

In our view, the ideal way to assess the within-cohort redistribution from a public program like Medicare or social security is to measure lifetime taxes and benefit streams for groups that enter adulthood on equal footing. One could push this further and break down the population into groups that were born on equal socioeconomic footing, although this approach would fold in the effects of childhood transfer programs. The more general lesson of our research is the importance of asking critical empirical and theoretical questions about the measurement of lifetime poverty when analyzing the welfare impacts of old-age transfer programs.

APPENDIX

A Mortality Estimates

We estimate education- and sex-specific life tables for those under age 65 using the Human Mortality Database combined with the NMFS. We use the MCBS for those at or over age 65.

A.1 Population Under 65

The nationally representative NMFS contains individual-level data on a sample of decedents from 1992, 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 NMFS population weights, we 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.

Table A-1 shows our estimated death rates for different age, sex, and education groups, calculated from the NMFS, using the NHIS as the population denominator. 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 Human Mortality Database provides age- and sex-specific death rates by single year of birth, beginning in 1959 and (currently) ending in 1998. For example, we know death rates from age 28 to 67 for the 1931 birth cohort, from age 27 to 66 for the 1932 birth cohort, and so on up to the 1941 birth cohort, where we know death rates from age 18 to 57. To construct the combined age-specific death rates for the 1931-41 birth cohort as a whole, we average over all available birth years between 1931 and 1941. For example, the age 26 death rate is the average death rate across cohorts born between 1933 and 1941. Combining these with the ratios in Table A-1 yields age-, sex-, and education-specific death rates up to age 65. These in turn imply survival curves up to age 65.

A.2 Population Over Age 65

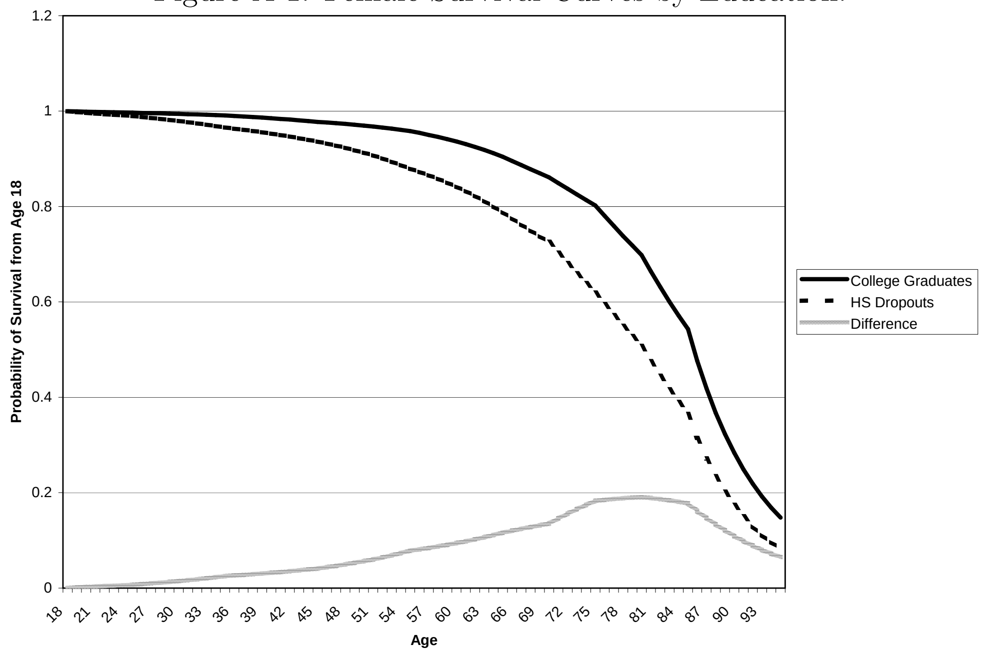
For people at or over age 65, we use the MCBS to estimate sex- and education-specific death rates for each single year of age between 65 and 95 (we topcode age at 95 in the MCBS data, due to a sparsity of single-year age observations above this point). These death rates directly imply survival curves for ages over 65. The 1931-41 birth cohort ranged between ages 51 and 68 over the MCBS sample period. Therefore, the very youngest piece of the MCBS sample represents our cohort of interest. With this calculation, we assume that the

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

	Age Group	High Sch Dropouts	High Sch Grads	College Attendees	College Grads	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 A-1: Female Survival Curves by Education.



older cohorts in the MCBS have similar death rate differentials to the 1931-41 birth cohort, which has not yet revealed its true differential death rate patterns.

A.3 Results

The survival curves for women associated with these death rates and life tables are shown in Figure A-1. As discussed in the text, socioeconomic differences are not as large for women as they are for men.

B MCBS data

B.1 Description of Data

The MCBS contains detailed data on health expenditures and especially on Medicare expenditures. MCBS respondents are linked to Medicare administrative data on claims.[25] 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.[26] The sum of the two represents Medicare's total outlay on each individual. A detailed description of sample sizes in the MCBS appears in Table A-2.

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

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

[26] 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.

Table A-2: Sample Sizes by Age, Sex, and Educational Attainment in the 1992-99 MCBS surveys.

	Males				Females			
Age Group	HS Dropout	HS Grad	Coll Attendee	Coll Grad	HS Dropout	HS Grad	Coll Attendee	Coll Grad
18-29	342	428	65	7	153	261	71	15
30-39	1022	996	305	100	473	595	297	80
40-44	646	553	285	86	376	357	192	85
45-49	480	335	199	68	311	230	105	68
50-54	539	306	110	62	334	248	133	68
55-59	665	428	146	72	443	291	132	51
60-64	1,201	729	373	360	1,002	908	349	163
65-69	3,054	2,565	1,364	1,890	3,490	3,756	1,725	1,051
70-74	2,577	2,002	1,076	1,280	3,073	3,232	1,537	905
75-79	2,685	1,681	906	1,048	3,743	2,912	1,427	876
80-84	2,662	1,331	696	837	4,549	2,717	1,273	853
85+	2,255	651	452	483	4,858	2,099	1,140	870

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.

We also decompose Medicare HMO payments into Part A and B components. 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. Fortunately for us, Medicare explicitly decomposes its HMO payments into Part A and B components. To construct our decomposition, we use Medicare's explicit payment schedules, which are a matter of public record. Medicare's Part A and B payments to HMO's are determined each year as a function of the individual's age, sex, county of residence, coverage by employer-based insurance, coverage by Medicaid, and ESRD (end-stage renal disease) status. Since we have data from Medicare on the specific payment schedule from 1992 to 2002, and since the MCBS reports all the relevant characteristics for each individual, as well as monthly[27] data on whether an individual is enrolled in an HMO, we explicitly calculate the monthly Part A and Part B payments made by Medicare to HMO's for all respondents in HMO's. We were able to validate this procedure, because the 1995-1999 MCBS waves report the HMO premium actually paid by each respondent. We confirmed that our constructed premia matched the reported premia in every case, within rounding error (of one penny).

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

[27]In the MCBS, the data on ESRD status, institutionalization status, and employer-based health insurance coverage are also available monthly from Medicare administrative data.

physician payments, and the hospital wage-price index used to deflate hospital payments. The physician GPCI's are used by Medicare to adjust expenditures for differences in area labor costs, practice expenses, and malpractice expenses. The wage-price indices are used to adjust hospital expenditures for differences in labor cost. Due to the exclusion of capital costs (which account for an average of 30% of hospital expenditures), the standard practice is to use (0.7)*(Wage Index)+(0.3) as an index of total hospital expenditures. We adopt this convention. Both indices were matched to beneficiaries in the MCBS sample 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 (BEA) data on per capita personal income at the county and state level, available by year. 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.[28] 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.2 Survival-Adjusted Benefits Profile

The impact of survival alone can be made clear if we adjust the Medicare benefits profile by survival. Multiplying each number in Table 1 by the relevant survival probability results in A-3 The table demonstrates that the advantage of the poorer groups in absolute terms is largely eroded by differential mortality, although the differences are still far below the corresponding gradients in taxes paid.

B.3 Calculating Lifetime Benefits

The lifetime benefits calculation begins with a full profile of benefits, from age 18 onwards. Table A-4 displays per capita Medicare benefits over the life cycle, computed from the MCBS. The per capita benefits figures for those under 65 are obtained using both the MCBS and the CPS. The MCBS is used to compute average benefits for individuals eligible for Medicare benefits. The 1992-99 CPS are used to compute, by age, sex, and education cell, the proportion of the population receiving Medicare benefits. The two numbers together represent per capita benefits in each age-sex-education group.

We cannot simply apply the lifetime survival profiles to the *cross-sectional* Part A benefits profiles in Table A-4. The benefits that will be received by the 1931-41 birth cohort—our cohort of interest—will grow over time, past the levels that are currently observed in

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

Table A-3: Real Per Capita Medicare Benefits by Educational Attainment, adjusted for survival probabilities.

		Males				Females			
		High Sch Dropouts	High Sch Grads	College Attendees	College Grads	High Sch Dropouts	High Sch Grads	College Attendees	College Grads
Total Medicare	65-74	$2,553	$2,433	$2,599	$2,658	$3,056	$2,520	$2,532	$1,860
	75-84	$1,884	$2,435	$2,764	$3,156	$2,939	$3,094	$3,254	$2,934
	85+	$584	$921	$1,104	$1,368	$1,455	$1,577	$1,683	$1,757
Medicare Part A	65-74	$1,708	$1,516	$1,564	$1,619	$1,928	$1,582	$1,555	$989
	75-84	$1,213	$1,596	$1,668	$1,928	$1,966	$2,025	$2,120	$1,806
	85+	$412	$669	$790	$928	$1,045	$1,138	$1,148	$1,277
Medicare Part B	65-74	$557	$540	$524	$630	$825	$538	$497	$495
	75-84	$424	$525	$713	$887	$705	$667	$692	$703
	85+	$107	$158	$187	$290	$288	$292	$318	$339
Medicare HMO	65-74	$288	$378	$510	$409	$303	$401	$480	$376
	75-84	$247	$315	$382	$341	$267	$402	$442	$425
	85+	$65	$93	$127	$150	$122	$147	$217	$141

Source: MCBS, 1992-1999.

Notes: All values are per capita real 1997 dollars.

Table A-4: Real Per Capita Medicare Benefits by Educational Attainment over the life-cycle.

	Males				Females			
Age Group	HS Dropout	HS Grad	Coll Attendee	Coll Grad	HS Dropout	HS Grad	Coll Attendee	Coll Grad
18-29	$21.62	$14.93	$4.63	$0.00	$49.21	$19.50	$8.13	$0.03
30-39	$100.29	$28.51	$20.34	$20.88	$70.58	$25.18	$35.26	$17.05
40-44	$165.76	$56.45	$46.04	$27.26	$73.00	$24.76	$39.05	$17.55
45-49	$152.94	$61.32	$60.85	$20.24	$97.66	$41.63	$31.60	$20.55
50-54	$168.40	$109.80	$90.83	$101.06	$177.55	$69.79	$45.77	$18.42
55-59	$323.49	$141.42	$172.93	$46.15	$189.46	$119.16	$170.93	$33.93
60-64	$516.62	$224.20	$101.70	$53.28	$296.70	$93.16	$166.72	$40.84
65-69	$2,753	$1,810	$1,813	$1,598	$2,491	$1,783	$1,505	$883
70-74	$3,493	$2,934	$2,768	$2,519	$2,868	$2,256	$2,358	$1,428
75-79	$3,684	$3,525	$3,800	$3,261	$3,554	$2,900	$3,233	$2,497
80-84	$4,494	$4,680	$3,819	$3,705	$4,243	$4,251	$3,619	$2,710
85+	$5,161	$5,742	$5,288	$4,803	$5,385	$5,045	$3,887	$4,147

Note: All figures are stated in terms of constant 1997 dollars. They include Part A fee-for-service benefits as well as premia paid by Medicare to Medicare HMO's for Part A services. The total sample is 96,280 person-years: details are in Appendix B.

the MCBS. Therefore, we calculate the expected value of Medicare benefits under various assumptions about future real growth in Medicare benefits.

Suppose Medicare benefits are assumed to grow at some rate X. We construct the lifetime path of benefits by first assuming that the real Part A benefit data from 1992-99 approximately represent the benefits the 1931-41 cohort will be receiving exactly at age 65. (We make the same assumption for benefits received under age 65.) We then suppose that benefits will be $X\%$ higher at age 66, an additional $X\%$ higher at age 67, and so forth. If B_{it} represents the average observed benefit of group i at age t, we construct the age t benefit as $B_{it} * (1 + \frac{X}{100})^{t-65}$.[29] 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.[30]

B.4 Calculating Family Benefits

To impute family benefits from the MCBS, we maintain the assumption from the HRS calculations that families are formed through marriage and dissolved only at the death of one spouse. Therefore, our task is to impute the Medicare benefits received by an individual as well as his current spouse, or his living ex-spouse.[31] When we alter our life-cycle sharing rule in Appendix D, we calculate rates of return based only on individual Medicare benefits. The analysis there serves as a check on the importance of the family benefits imputation also.

To impute the average family Medicare benefit for, say, X year-old college-educated males, we use the proportion (in the MCBS) 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 (or ex-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.

B.5 Accounting for Part B

The previous analysis accounts for the lifetime value of Part A. Unfortunately, we cannot produce similar estimates for Part B, because we do not have lifetime data on federal income tax payments for the HRS cohort. Since Part B of Medicare is funded out of general federal revenues, this limitation makes it impossible for us to estimate the exact rates of return

[29]Specifically, B_{it} is estimated within the following age intervals: 65-69, 70-74, 75-79, 80-84, and 85+. Within each interval, real benefits are assumed to be constant. We group the data within intervals to smooth out estimated benefits, because the data are too sparse to estimate benefits for every single age group reliably.

[30]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.

[31]Since virtually no elderly people get married for the first time, we do not consider the problem of benefits for potential spouses.

Table A-5: Expected Present Value of Part B Benefits Net of Premia for a Family, 4% Annual Growth.

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%	$45,828	$50,998	$57,580	$64,375	$44,491	$44,304	$48,677	$49,588
1%	$25,542	$28,098	$31,565	$35,082	$24,805	$24,390	$26,689	$27,096
2%	$14,430	$15,674	$17,509	$19,339	$14,042	$13,602	$14,824	$14,980
3%	$8,268	$8,854	$9,827	$10,780	$8,082	$7,684	$8,342	$8,378
4%	$4,808	$5,065	$5,579	$6,075	$4,737	$4,400	$4,758	$4,739
5%	$2,842	$2,936	$3,205	$3,460	$2,834	$2,554	$2,752	$2,711

Note: All figures are in real 1997 dollars, from the point of view of an 18 year-old.

on Medicare Part B. However, we do have enough data to show that, given the negative gradients in its benefit structure, Part B is likely to be progressive as well.

We cannot estimate internal rates of return, but we can produce bounds on the standard tax incidence calculation. The net present value of Medicare for group i is given by Equation 2.1. If this net present value represents a larger share of income for poorer groups, the program is progressive according to the standard tax incidence view of progressivity. We can take this approach to show that, at a minimum, Medicare is progressive, although we cannot quantify the exact extent of the progressivity. Our strategy is to show that net present value, in terms of (Lifetime Benefits - Lifetime Premia) - Lifetime Tax Payments, is falling with lifetime income. To do so, we will show that (Lifetime Benefits - Lifetime Premia) rises across education groups more slowly than lifetime income, and that Lifetime Tax Payments rise more rapidly than lifetime income across education groups.

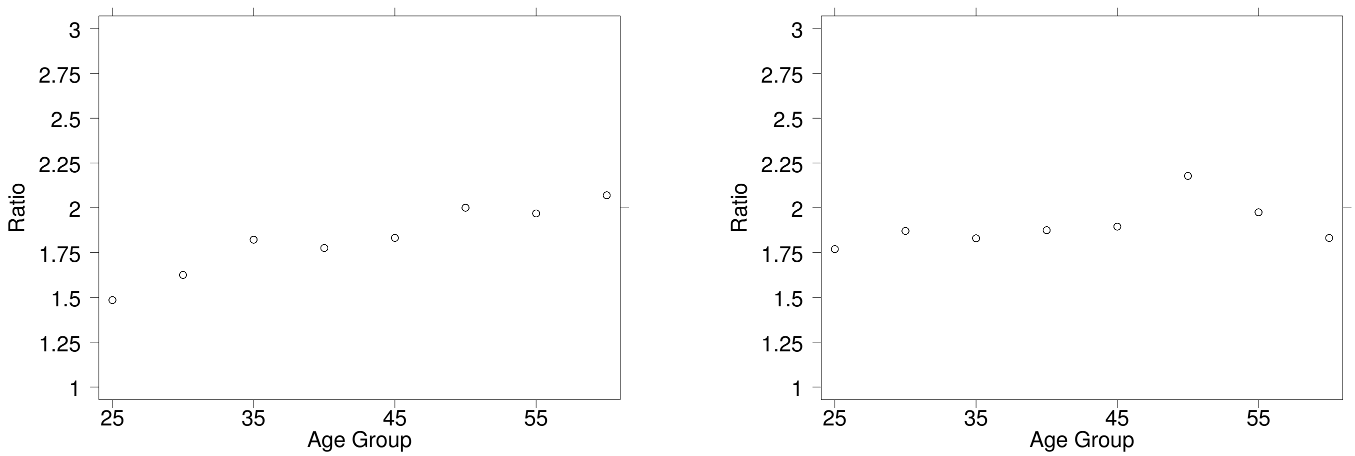
First, we use the MCBS data to calculate directly the expected present value of Medicare Part B benefits, net of Part B premia paid by elderly beneficiaries.[32] Our estimates suggest that the expected present value of Part B benefits represents a larger share of lifetime income for high school dropouts than college graduates. Moreover, the progressivity of the federal tax system implies (and we will show empirically) that expected present income tax liabilities represent a smaller share of lifetime income for high school dropouts. These two results taken together imply that Part B is progressive under the tax incidence view of progressivity.

Data on Part B benefits are taken directly from the MCBS. Appendix B describes how we identify Part B expenditures. The MCBS also allows us to calculate the actual Part B premia paid by respondents, because it reports the number of months each respondent paid for Part B. We combine these data with *Federal Register* information on the monthly Part B premia charged, from 1991 to 1998 (the years covered by the 1992-99 MCBS surveys). We check these calculations against actual premia paid, which are reported in the 1995-99 MCBS. For every observation, our estimates are within rounding error (to the nearest penny) of the data reported in the MCBS.

Table A-5 depicts what the family of the average individual in the given sex-education category can expect to receive from Medicare Part B benefits alone, net of actual premia. These figures assume a 4% rate of benefit growth (premia are assumed to grow at the same

[32]We net out premia, because the portion of Part B financed by premia does not represent a return on taxes paid.

Figure A-2: Age-Specific Family Income Ratio of College Graduates to High School Dropouts, 1975



(a) Males

(b) Females

rate as benefits), and are discounted to the point of view of an 18 year-old. At a real interest rate of 3%, male college graduates can expect to receive approximately 34% more from Part B than high school dropouts, while female college graduates can expect to receive about 23% more. While these gradients are significant, they are not as large as the gradient in expected lifetime income across these groups.

To gain an appreciation for the gradient in expected lifetime income, we will make some conservative assumptions. First, suppose that mortality rates do not differ across education groups. In reality, differential mortality works to lower the relative lifetime income of the less educated. Ignoring this, we can look at annual gradients in lifetime income without adjusting for survival. Second, consider the gradient in family income for 1975, which exhibits the most compressed family income gradients over the entire period 1965-2001.[33] The family income gradients observed in 1975 provide a lower bound on the expected lifetime income gradients.

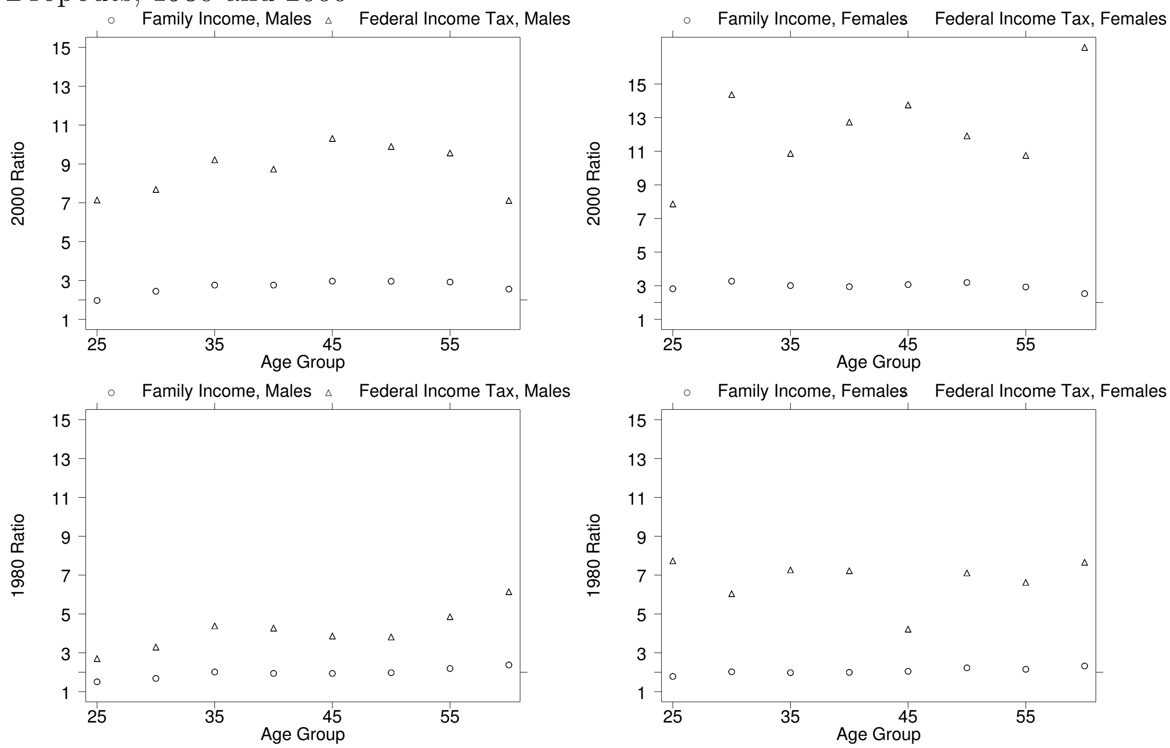
Using the Current Population Survey (CPS), we calculate average family income by education and sex, for 5-year age intervals. Figure A-2 depicts the results for the 1975 CPS. The figure shows that the family income ratio is uniformly above 1.5, even for this most compressed of years. This conservative 50% income gradient exceeds the difference in expected Medicare benefits, which is under 30%. Therefore, the expected net present value of benefits represents a larger share of income for poorer groups.

The calculations above show that Part B is progressive on the benefit side. As a result, it must be progressive as a whole, since it is funded by the progressive federal income tax system. The Congressional Budget Office reports that for the 1979-1997 period, the lowest quintile of taxpayers pay less than zero tax, while the highest quintile pay approximately 15% of their income (Congressional Budget Office, 2001).

While the data are not as high-quality as the CBO data, the CPS (from 1980 through the

[33]This statement is based on the authors' calculations using the CPS.

Figure A-3: Age-Specific Federal Tax and Income Ratios of College Graduates to High School Dropouts, 1980 and 2000



present) itself contains imputations of federal tax liabilities, based on self-reported income data and other federal data sources from the IRS. [34] Using these data, we can estimate the gradient in taxes across education groups, rather than quintiles of the income distribution.

The top two panels of Figure A-3 depict the gradients for the year 2000, while the bottom two depict 1980. The left-hand panels display the data for males, while the right-hand ones show them for females. In every instance, the gradient in taxes paid is steeper than the gradient in income. There has been some expansion in the progressivity of the income tax system over the past 20 years, particularly for males. The figure illustrates empirically the legislated progressivity of the federal income tax system.

B.6 Trends in Progressivity

Table A-6 summarizes trends in progressivity over the life of our sample. From 1992 to 1997, benefits became more progressive for women—who represent the majority of aged Medicare beneficiaries—but there was a partial retrenchment thereafter. This is consistent with the findings of Lee et al. (1999). We do not find a similar increase in progressivity for males.

[34]The CPS data have three important limitations, relative to the CBO estimates. First, the CPS does not collect data on itemized deductions and capital gains, both of which the CBO imputes. Second, the CPS data are topcoded. Finally, CPS incomes differ significantly from incomes reported on tax returns, which are believed to be more reliable. CBO adjusts the CPS data to bring it in line with tax return data.

Table A-6: Changes over time in real per capita Medicare benefits by Educational Attainment.

		Males				Females			
		High Sch Dropouts	High Sch Grads	College Attendees	College Grads	High Sch Dropouts	High Sch Grads	College Attendees	College Grads
	1992	$4,367	$3,712	$3,814	$3,677	$4,474	$3,390	$3,218	$2,658
	1993	$5,285	$3,799	$4,073	$3,877	$4,663	$3,418	$3,447	$2,837
	1994	$5,298	$4,012	$3,496	$3,605	$4,966	$3,645	$3,539	$3,026
	1995	$4,584	$4,320	$4,204	$3,012	$5,787	$4,209	$4,303	$2,717
	1996	$5,999	$4,055	$4,533	$3,419	$5,416	$3,914	$3,990	$3,071
	1997	$5,124	$4,764	$5,715	$4,053	$5,610	$3,738	$3,957	$3,173
	1998	$5,535	$4,558	$4,157	$3,902	$4,941	$4,187	$3,380	$3,119
	1999	$4,897	$4,702	$4,149	$4,668	$5,093	$4,598	$3,834	$3,054
1992	65-74	$3,653	$3,181	$3,309	$3,259	$3,589	$2,551	$2,515	$1,254
	75-84	$5,070	$4,814	$4,277	$4,671	$4,715	$4,303	$4,588	$4,237
	85+	$5,973	$4,800	$7,817	$4,450	$6,403	$6,429	$3,494	$5,782
1999	65-74	$4,335	$3,871	$3,431	$3,433	$4,507	$3,662	$3,127	$2,348
	75-84	$5,286	$5,467	$5,052	$5,834	$5,079	$4,980	$4,401	$3,450
	85+	$6,048	$8,571	$5,467	$10,216	$6,291	$7,603	$4,967	$5,156

Source: Elderly (65+) beneficiaries in the 1992-99 MCBS.

To explore the impact of these progressivity shifts on our calculations, we compute—for individuals—the present value of Medicare Part A benefits, and the present value of Medicare Part B, using only the 1992 MCBS data, which exhibits the least progressive benefit structure. The results for Part A are depicted in Table A-7.

Comparing Table A-7 to Table 2, which is based on all available MCBS data, reveals an increase in progressivity for females over the 1990s, but little change for males: among females, college graduates receive a larger percentage premium in the 1992 data. This is consistent with our finding that the shift in benefits seemed to take place more for females than for males in our data. Of course, from a family perspective, progressivity would have grown for both sexes over the course of the 1990s. However, the size of the shift is quite small relative to the gradient in net dollar flows shown in Table 4, and is certainly not enough to reverse our finding of progressivity for either sex.

Similar findings obtain for Part B, which also became more progressive over the 1990s, but which was still progressive under its 1992 benefit structure. Using the 1992 data, we find—for males—that college graduates received 38% more expected present value benefits than high school dropouts at a 3% real rate of interest. This is still less than our conservative estimate of a 50% higher lifetime income for this group. For females, the present-value advantage of college graduates was lower, and progressivity was higher from an individual perspective.

Table A-7: Net Dollar flows to individuals from Medicare Part A, based on 1992 Medicare experience.

	Real Interest Rate	Male				Female			
		Less than HS	HS Grad	Coll Attendee	Coll Grad	Less than HS	HS Grad	Coll Attendee	Coll Grad
No Growth	0%	$37,788	$21,308	$12,145	$6,995	$4,068	$2,388	$36,914	$35,098
	1%	$38,111	$21,405	$12,154	$6,975	$4,043	$2,366	$20,403	$18,944
	2%	$37,224	$20,870	$11,832	$6,781	$3,926	$2,296	$11,400	$10,348
	3%	$45,693	$25,543	$14,441	$8,253	$4,765	$2,779	$6,436	$5,720
	4%	$4,890	$4,792	$4,997	$4,946	$3,816	$3,790	$3,671	$3,198
	5%	$2,880	$2,777	$2,895	$2,850	$2,205	$2,167	$2,115	$1,808
4% Ann. Growth	0%	$60,386	$61,997	$60,988	$75,893	$67,405	$73,829	$63,586	$66,873
	1%	$33,306	$34,030	$33,417	$41,422	$36,235	$39,187	$34,438	$35,273
	2%	$18,584	$18,901	$18,527	$22,885	$19,728	$21,065	$18,860	$18,828
	3%	$10,486	$10,619	$10,390	$12,793	$10,874	$11,465	$10,442	$10,168
	4%	$5,981	$6,032	$5,892	$7,232	$6,066	$6,317	$5,843	$5,555
	5%	$3,447	$3,463	$3,377	$4,134	$3,424	$3,523	$3,303	$3,070

Note: All figures are in real 1997 dollars, from the point of view of an 18 year-old. Calculations are based on 1992-99 MCBS, and mortality data from NMFS.

C 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 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.

C.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.

C.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

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

	Presence in Earnings History File			
Marital Status in 1991	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

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 A-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.[35] 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 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

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

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.

C.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 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 A-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.

C.4 Taxes Across the Income Distribution

Mechanically, the tax gradient across the realized lifetime income distribution is steeper than across the education distribution, simply because taxes depend directly on actual lifetime

Table A-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%
1966	30-34	2.2%	4.8%	2.2%	2.9%	1.4%	1.9%	7.8%	0.8%
1966	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%
1982	45-49	6.9%	12.6%	11.5%	9.1%	8.7%	4.3%	3.8%	9.9%
1982	50-54	8.4%	9.1%	8.4%	16.1%	4.0%	3.2%	3.7%	5.7%

Source: Current Population Surveys, 1966-82.

income. To demonstrate the impact of this, we calculated average annual individual Medicare taxes paid, between 1966 and 1989, for HRS men who were between the ages of 30 and 34 in 1966. For this same set of people and period of time, we constructed average annual (covered) earnings. We then compared average annual taxes across the education distribution, to taxes across the average annual earnings distribution.

In this sample, 26% of people were high school dropouts, 33% high school graduates, 18% college attendees, and 23% college graduates. Therefore, we compared taxes for high school dropouts to taxes paid by the bottom 26% of the average annual income distribution; we compared high school graduates to people between the 26th and 59th percentile of the annual earnings distribution, and so on.

The results are depicted in figure A-4. As we hypothesized, the gradient in taxes paid is much steeper across the lifetime earnings distribution than across the education distribution. Average taxes paid differ by a factor of three between the top and bottom earnings groups, but they differ by less than a factor of two between the top and bottom education groups.

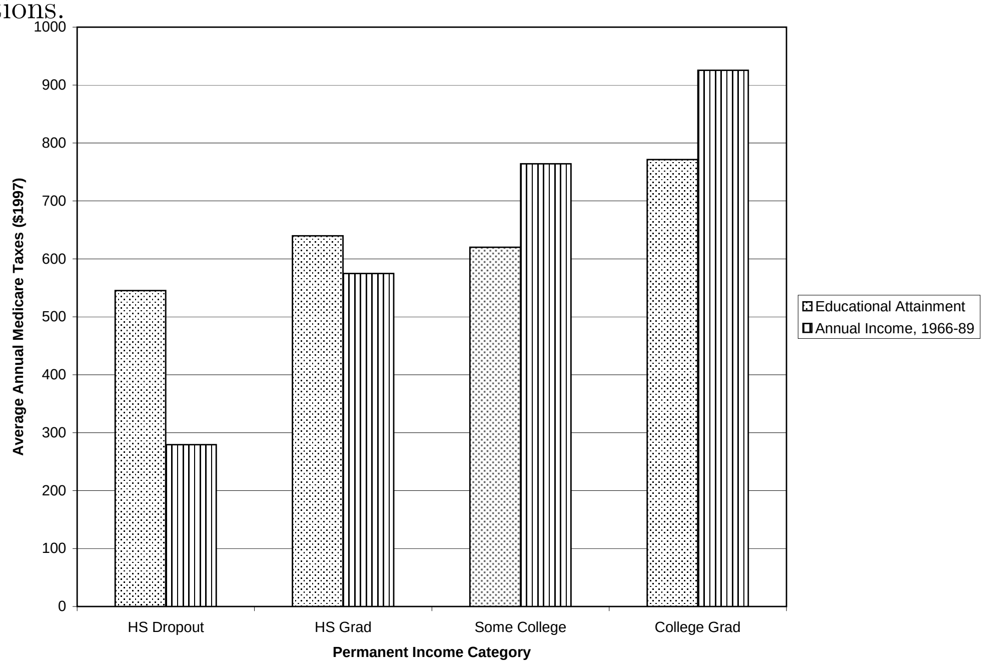
D CPS Data

To assess the sensitivity of our results to the assumption that family tax burdens are perfectly shared by a couple, we used CPS data to re-estimate rates of return under the assumption that taxes were perfectly divided between spouses. In this appendix, we discuss how the CPS data were processed and analyzed.

D.1 Matching Spouses

The most difficult part of using the CPS data is matching spouses. To aid in this task, the CPS provides a "household relationship" variable, which indicates whether the individual is a head of the family, or the spouse of the head. The CPS also identifies family units. We identify spouses as the individuals (of opposite sex) reporting that they are married, with spouse present, within a single family (or subfamily). Since the CPS defines a family around a single married couple, this procedure works in the vast majority of cases. However, there are a few problematic years: 1966, 1967, and 1972. Apart from these years, there are a total of 276 observations that appear to be in families with more than 2 spouses (the entire

Figure A-4: The Distribution of Annual Medicare Taxes across the Education and Earnings Distributions.



CPS data set has more than 2 million observations). However, there are 9277 problematic observations in 1966, 4478 in 1967, and 43,474 in 1972. The problem in 1972 appears to be duplicate family or subfamily identifiers: there are many instances of 4 and 6 spouses within a single family. For the other two years, the CPS identified households, but not subfamilies within households; the problematic observations thus could arise in extended families. Excluding these years from our calculations has little effect. All the results in the paper include them, but randomly match spouses within "families" as identified by the CPS.

D.2 Pre-1964 data

The HRS Earnings History file goes back to 1951, but the CPS only goes back to 1964. To make the average tax calculations comparable, we must account for the fact that the 1931-41 birth cohort did not have to pay Medicare taxes for some portion of its working life, prior to 1964. We simply construct data files for 1951-63 in which covered income is set to zero, but the one complication is how to weight observations in the pre-1964 years for the CPS. Essentially, we assume that the composition of the cohort remains fixed at its 1964 level. This ignores some differential mortality, but since the cohort is relatively young at this point of time, this bias ought not to be severe.

D.3 CPS Analysis

Partly as a result of data limitations, the earlier analysis takes the life-cycle view of perfect sharing of wealth, taxes, and Medicare benefits between spouses. Using different data, we now take the opposite view, that couples share wealth and taxes as little as possible. In particular, we now assume that unmarried people do *not* share with potential spouses, divorced people do not share with ex-spouses, and married couples share exactly half of their wealth and taxes. This strategy obviates the need to impute tax data for an unobserved ex-spouse or future spouse, and the need to impute family-level Medicare benefits from the MCBS. The reality of income-sharing within the family presumably lies somewhere between these two extremes of life-cycle sharing and this rather individualistic view.

By using data from the 1966-2000 Current Population Surveys (CPS), we are able to implement this analysis (Appendix D describes the processing of these data in more detail). Unlike the HRS, the CPS contains data on marital status at every point in time. Since we know with certainty whether or not individuals are married, we can apportion total family taxes into one half borne by the husband and another half borne by the wife. The two important drawbacks of the CPS are its use of self-reported rather than administrative wage data,[36] and the need to construct a synthetic 1931-41 birth cohort,[37] rather than the actual cohort present in the HRS.

From the 1966 through 2000 CPS data,[38] we select every household in which at least one person belongs to the HRS cohort. Within each household, we match each individual to his/her spouse if present and calculate the total Medicare payroll taxes paid by the couple. The tax burden of each couple is then split in half and assigned to each partner. If a spouse is absent but married (that is, not divorced, deceased, or separated), we impute spousal wage income within single-year age, sex, and education cells.[39] In the CPS, this affects just three to four percent of the total observations on spousal income; in comparison, the rate of imputation is about twenty percent in the HRS.

Table A-10 displays the resulting estimates of the per-person lifetime Medicare tax liability. It is not possible to compare these numbers directly with the family taxes paid in Table 3, but it is possible to make some rough comparisons. Approximately, average family income should be about twice as high as individual income. Even if the data were perfect, this would not hold exactly, because not everyone is married, and spouses are not always identically educated. Nonetheless, this simple rule of thumb seems to work fairly well. Departures from the rule invariably seem to suggest underreporting of taxes in the CPS, relative to the HRS. Indeed, earnings profiles in the CPS are slightly lower than in the HRS administrative data. This could be the result of self-reporting bias, or of mistakes in the administrative data. Fortunately, this difference does not appear to affect progressivity.

This phenomenon also appears in the expected net present value of Medicare and the associated internal rates of return. Table A-11 displays the net present flows of Medicare to individuals, assuming that Medicare taxes are split evenly between spouses. According to

[36]This is not to imply that administrative data are perfect, but they are likely to be better than self-reported data, because individuals and the government have incentives to correct mistakes in administrative data.

[37]In one respect, the use of the synthetic cohort is valuable, because it helps assess the impact of survivorship bias in the HRS cohort.

[38]These surveys yield a profile of Medicare payroll taxes exactly as long as the HRS profile.

[39]For example, if there is a 40 year-old, white high school graduate male (married, divorced, or separated) with an unobserved spouse, we assign to him the spousal income observed for other 40 year-old, white high school graduate males.

Table A-10: Expected Net Present Value of Medicare Payroll Tax Liability faced per Person, 1931-41 birth cohort.

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%	$9,609	$14,876	$17,895	$25,217	$7,968	$13,592	$16,955	$23,093
1%	$7,152	$10,991	$13,168	$18,151	$5,962	$10,066	$12,456	$16,802
2%	$5,383	$8,212	$9,800	$13,221	$4,510	$7,536	$9,254	$12,365
3%	$4,097	$6,205	$7,376	$9,745	$3,448	$5,703	$6,951	$9,204
4%	$3,151	$4,739	$5,612	$7,267	$2,664	$4,361	$5,278	$6,927
5%	$2,448	$3,657	$4,315	$5,481	$2,078	$3,368	$4,050	$5,271

Note: All figures are in real 1997 dollars. Calculations are based on data from the 1966-2000 CPS.

Table A-11: Expected Net Present Dollar Flows from Medicare Part A for Individuals in the HRS Cohort, 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%	$24,478	$23,772	$23,243	$20,526	$42,687	$35,082	$32,553	$18,950
	1%	$12,190	$10,517	$9,672	$7,116	$22,127	$16,639	$14,672	$5,895
	2%	$5,712	$3,892	$3,026	$894	$11,253	$7,291	$5,787	$32
	3%	$2,337	$682	-$92	-$1,772	$5,502	$2,626	$1,485	-$2,354
	4%	$618	-$779	-$1,432	-$2,715	$2,475	$370	-$494	-$3,100
	5%	-$218	-$1,357	-$1,892	-$2,856	$906	-$651	-$1,308	-$3,108
4% Ann Growth	0%	$43,712	$50,296	$52,247	$54,234	$79,243	$73,570	$72,094	$56,807
	1%	$22,436	$24,481	$24,885	$24,759	$41,211	$36,625	$35,195	$25,384
	2%	$11,230	$11,321	$11,093	$10,227	$21,324	$17,780	$16,555	$10,171
	3%	$5,339	$4,675	$4,230	$3,217	$10,873	$8,188	$7,195	$2,975
	4%	$2,268	$1,389	$908	-$21	$5,370	$3,350	$2,566	-$270
	5%	$698	-$168	-$612	-$1,387	$2,482	$962	$349	-$1,591

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

Table A-12: CPS-Based Internal rates of return on Medicare Part A by sex, education group, and rates of growth in Medicare benefits.

Medicare	Males					Females				
Benefit	High Sch	High Sch	College	College		High Sch	High Sch	College	College	
Growth	Dropouts	Grads	Attendees	Grads	Overall	Dropouts	Grads	Attendees	Grads	Overall
0%	4.7%	3.4%	3.0%	2.2%	3.2%	6.2%	4.3%	3.7%	2.0%	4.3%
1%	5.0%	3.7%	3.3%	2.7%	3.6%	6.5%	4.7%	4.1%	2.5%	4.7%
2%	5.3%	4.1%	3.7%	3.1%	4.0%	6.9%	5.0%	4.5%	2.9%	5.1%
3%	5.6%	4.5%	4.1%	3.6%	4.3%	7.2%	5.4%	4.9%	3.4%	5.5%
4%	5.9%	4.8%	4.5%	4.0%	4.7%	7.5%	5.8%	5.3%	3.9%	5.8%
5%	6.2%	5.2%	4.9%	4.4%	5.1%	7.8%	6.2%	5.7%	4.3%	6.2%

the CPS tax data, the value of Medicare is higher for most groups, except perhaps for the least educated males. The values in this table tend to be a bit higher than those in Table 4. Of course, we are measuring slightly different concepts in each table: this table reflects the value per person, while Table 4 measured the value for the average family. The scale in both tables should be roughly similar, however, because Table A-11 is based on approximately half the tax payments and approximately half the benefits. The slightly higher values of Medicare are consistent with the lower earnings and tax payments in the CPS data. Notice, however, that the gradient across education groups remains unchanged. Medicare continues to be more valuable in absolute terms to less educated groups.

Table A-12 displays the estimated internal rates of return based on the CPS data. These tend to be a few tenths of a percentage point higher overall than the HRS-based numbers in Table 5, probably because earnings profiles in the CPS are slightly lower than in the HRS administrative data. This could be the result of self-reporting bias, or of mistakes in the administrative data. These data also tend to generate slightly larger spreads in the internal rates of return across education groups. Regardless, this difference does not affect the qualitative results of interest. We continue to find that the rate of return on Medicare falls for the most educated groups. Finally, it is interesting to note that the CPS figures are closer to our overlapping generations estimate of a 5.4% internal rate of return on Medicare. It is, of course, hard to draw conclusions from this, since our overlapping generations estimate should be seen as an unsophisticated benchmark.

E Aggregation

In this appendix, we first provide a more formal analysis of the difference between the education and zip code income measures. We then show that higher levels of aggregation result in a more positively sloped relationship between income and medical expenditures. Finally, we show that aggregate measures of education—just like aggregate measures of income—generate more positively sloped relationships between socioeconomic status and medical expenditures. This suggests the importance of aggregation, rather than education *per se*.

Table A-13: Age- and Sex-Specific Distribution of Education in the MCBS, 1992-99.

	Age	Educational Attainment: No HS	HS Attend	HS Grad	Some Coll	Coll Grad
Men	65-74	0.20	0.16	0.29	0.15	0.20
Men	75-84	0.28	0.18	0.25	0.14	0.16
Men	85+	0.40	0.19	0.17	0.12	0.13
Females	65-74	0.17	0.18	0.37	0.17	0.10
Females	75-84	0.26	0.20	0.31	0.15	0.09
Females	85+	0.35	0.20	0.23	0.13	0.10

Source: MCBS, 1992-99.

E.1 Zip Code Income Quintiles

A regression context can provide a more formal sense of the relationship between zip code income and education measures. To facilitate the comparison between education groups and zip code income quintiles, we divide the MCBS population into five education groups: no high school, some high school, high school graduates, some college, and college graduates. Unfortunately, these are not equally weighted quintiles, but for some age groups, they are close.

Table A-13 depicts the distribution of education across age- and sex-specific groups in the MCBS. For all except the oldest age groups, the bottom two education groups are roughly equivalent to quintiles. The group of high school graduates, however, tends to be larger than a quintile, while the two college groups tend to be smaller than quintiles. In making comparisons across the distributions of education and zip code income quintile, therefore, it is important to bear in mind that the size of the high school graduates group is often larger than the size of the third quintile, while the sizes of the two college groups are often smaller than the top two quintiles.

Using the zip code income quintiles and the five education categories, we estimate the following regressions separately for age and sex-specific categories:

$$McareTotal_{it} = \beta_0 + \beta_1 ZipQuint_{it} + \lambda_t + \epsilon_{it} \tag{A-1}$$

$$McareTotal_{it} = \gamma_0 + \gamma_1 Educ_i + \mu_t + \phi_{it} \tag{A-2}$$

$McareTotal_{it}$ represents individual $i's$ total Medicare expenditures (that is, Parts A and B) at time t.[40] $ZipQuint_{it}$ represents individual $i's$ quintile in the zip code income distribution at time t, where zip code income is always based on the income of zip codes in the 1990 Census. The variables λ_t and μ_t represent time-specific fixed-effects.

Table A-14 reports the results of these regressions, which are identical to the curves

[40] The differences between gradients are quite similar for the Parts A and B components as well.

Table A-14: Comparing Medicare gradients across Zip Code Income Quintiles and Education Groups.

	Age	Zip Income Quintile				Educational Attainment			
		2nd	3rd	4th	5th	HS Attend	HS Grad	Some Coll	Coll Grad
Men	65-74	-133	**-768**	-529	**-593**	-621	**-1179**	**-1322**	**-1615**
		(321)	(293)	(281)	(280)	(369)	(272)	(306)	(280)
	75-84	-214	**-706**	-389	-459	-470	-460	-552	**-987**
		(349)	(306)	(323)	(340)	(335)	(288)	(399)	(314)
	85+	-302	343	559	229	-287	233	-224	-756
		(505)	(541)	(561)	(516)	(566)	(536)	(587)	(482)
Women	65-74	**-516**	**-504**	**-932**	**-958**	275	**-675**	**-856**	**-1632**
		(220)	(216)	(194)	(204)	(275)	(199)	(234)	(203)
	75-84	-227	-236	-111	**-550**	256	**-428**	-442	**-1262**
		(250)	(251)	(247)	(247)	(300)	(203)	(258)	(249)
	85+	6	**-739**	261	-246	81	-403	**-1523**	**-1342**
		(337)	(312)	(351)	(325)	(399)	(313)	(342)	(405)

Source: MCBS, 1992-99.

Note: Data are for total (Parts A+B) Medicare expenditures, adjusted for regional price variation using the GPCI and the hospital wage-price indices. Numbers in the table are based on age- and sex-specific regressions of price-adjusted total Medicare expenditures on dummies for year, as well as dummies for either Zip Income Quintile or Educational Category. Numbers in bold are significant at the 95% level.

in Figure 2, except the regression estimates also remove a year-specific fixed-effect. The numbers in bold are significantly different from zero at the 5% level. As in the figure, the gradient across education groups is more steeply negative for women than for men, and more steeply negative for younger men than older men. However, considering that women account for 60% of the elderly Medicare population, and men between the ages of 65 and 74 account for another 20%, the bulk of the elderly Medicare population exhibits a significantly negative gradient across education groups. In contrast to the negative gradient across education groups, the gradient across zip codes is essentially flat among 65-74 year-old men and women over age 85.

To compare accurately the gradients for 65-84 year-old women, we estimated our regression across zip code income deciles. In the education distribution, the difference between the top decile (college graduates) and the bottom quintile (those with no high school) is about \$1839 for 65-74 year-old women. In contrast, the difference between the top zip code decile and the bottom zip code quintile is \$1162, less than two-thirds of the value across education groups. For 75-84 year-old women, the difference between the top education decile (college graduates) and the bottom quintile (those with no high school) is about \$1515. The analogous difference across zip codes is just \$360.

Finally, we should note that more accurate measurement of elderly income at the zip code level only seems to exacerbate the difference between zip code income quintile and education. Table A-15 compares gradients in zip code income quintile to quintiles in zip code elderly income. Specifically, we use the 1990 census to compute the proportion of elderly people in each zip code living in a household with more than \$35,000 in annual income, and form quintiles based on this proportion. We chose the cut-off of \$35,000 in order to form a distribution that divided into quintiles most evenly. The table demonstrates that, if anything, quintiles in elderly income result in an even more positively sloped relationship between Medicare expenditures and income. The one exception occurs for women over the age of 85, where the gradient is more negative for elderly income.

E.2 County Income Quintiles

Since the MCBS reports the county of residence for each respondent, we link the MCBS to Bureau of Economic Analysis (BEA) data on per capita income (described in Appendix B) 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 population weight.

Figure A-5 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 1, of the text. 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. Even in the MCBS, therefore, benefits fail to vary negatively across local income groups. 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.

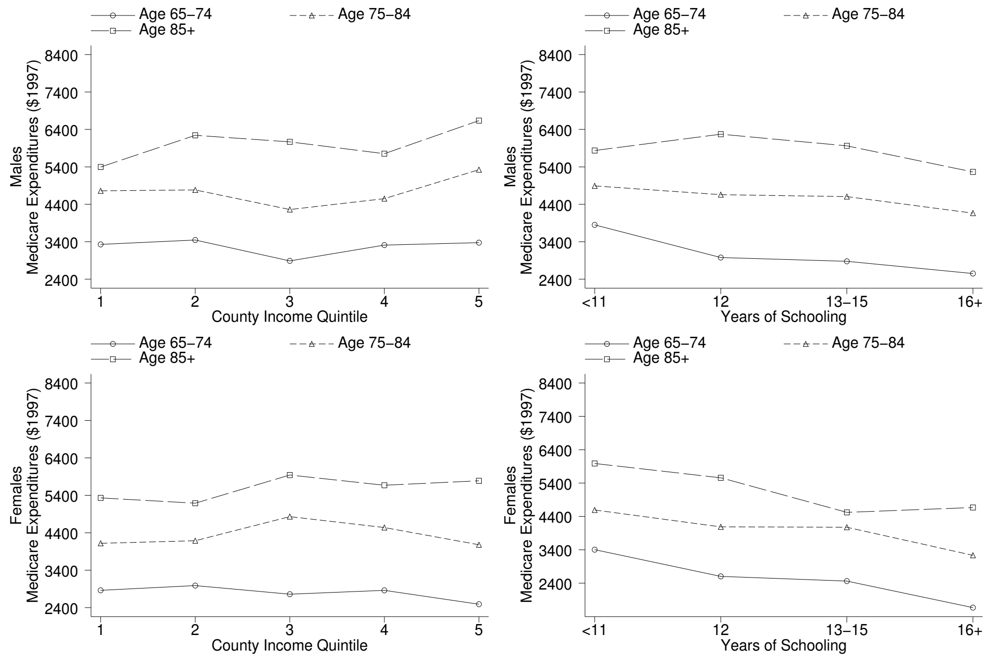
Table A-15: Comparing Medicare gradients across Zip Code Income Quintiles and Zip Code Quintiles for Elderly Income.

	Age	Zip Income Quintile				Elderly Poverty Zip Code Quintile			
		2nd	3rd	4th	5th	2nd	3rd	4th	5th
Men	65-74	-133	**-768**	-529	**-593**	460	143	95	-279
		(321)	(293)	(281)	(280)	(329)	(268)	(260)	(252)
	75-84	-214	**-706**	-389	-459	-229	-224	-214	-154
		(349)	(306)	(323)	(340)	(346)	(325)	(327)	(355)
	85+	-302	343	559	229	86	756	937	616
		(505)	(541)	(561)	(516)	(518)	(557)	(553)	(539)
Women	65-74	**-516**	**-504**	**-932**	**-958**	-150	-542	-345	**-669**
		(220)	(216)	(194)	(204)	(233)	(205)	(210)	(221)
	75-84	-227	-236	-111	**-550**	-370	-257	138	-429
		(250)	(251)	(247)	(247)	(257)	(265)	(258)	(262)
	85+	6	**-739**	261	-246	**-748**	-481	-142	**-912**
		(337)	(312)	(351)	(325)	(347)	(336)	(366)	(334)

Source: MCBS, 1992-99.

Note: Data are for total (Parts A+B) Medicare expenditures, adjusted for regional price variation using the GPCI and the hospital wage-price indices. Numbers in the table are based on age- and sex-specific regressions of price-adjusted total Medicare expenditures on dummies for year, as well as dummies for either Zip Income Quintile or Elderly Poverty Zip Code Quintile. Bold numbe are significant at the 95% level. "Elderly Poverty Zip Code Quintile" is the Zip Code's quintile in tl distribution of people over age 65 living in households with at least $35,000 in annual income.

Figure A-5: Per Capita Medicare Benefits Across Education Groups and County Income Quintiles.



E.3 County Education Quintiles

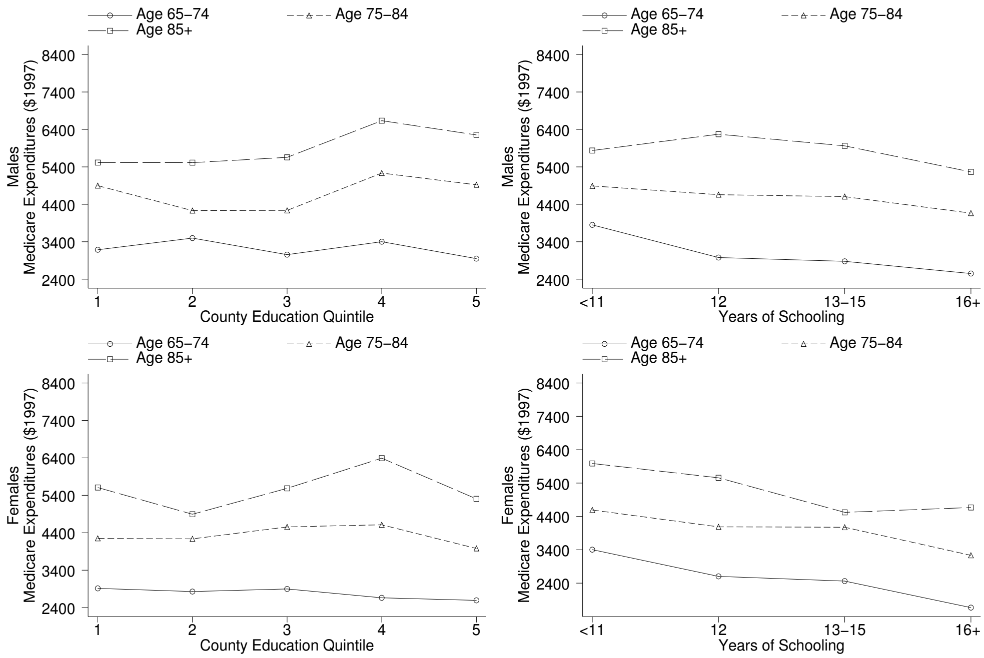
Perhaps our results owe themselves to the distinction between education and income, rather than to geographic aggregation bias. To assess this, we look at gradients across aggregate measures of education. Our results suggest that these are similar to geographically aggregated measures of income; the aggregation seems the key feature, rather than the use of education itself. Data from the 1990 Census (described in Appendix B) 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.[41] Since the MCBS contains data on county of residence, we can link these data to MCBS respondents. Based on the fraction of college graduates in 1990, we construct county education quintiles.[42]

The gradients across individual education groups and county education quintiles are shown in Figure A-6. From the top to the bottom education quintile, there is often no change, or a decline of less than a few hundred dollars. In contrast, the gradient across individual-level education often exceeds $1000 from the bottom group to the top. Moreover, while the gradient across individual education groups is almost always flat or negative, there are several instances of benefits rising across county education quintile. Qualitatively, Figure

[41]We obtained similar results for the proportion of high school graduates and the proportion of high school dropouts.

[42]One caveat to note is that we link the 1990 Census Data to the 1992-99 MCBS data and thus could be measuring county-wide education with error. However, our results for the 1992 MCBS are quite similar to those for the 1999 MCBS, suggesting that the expansion of measurement error over time does not affect the estimated gradients in benefits.

Figure A-6: Per Capita Medicare Benefits Across Education Groups and County Education Quintiles.



A-6 looks similar to Figure A-5, which depicts the gradient across county income quintiles. In both figures, the individual-level education measures generate a more negative and more consistently negative slope than the aggregated measures.

E.4 Comparing Education and Income Measures

Our interpretation of the evidence rests on the finding that similar individuals spend more on medical care when they live in richer areas. A simple and direct test of this is to regress Medicare expenditures on individual's education and zip code income quintile, as in Table A-16. Table A-16 shows the results of these regressions. Controlling for an individual's education, along with age, year, and sex, her zip code of residence has a significant effect on medical expenditures. People who live in richer zip codes incur higher Medicare expenditures than others. There is an annual difference of $319 between the top and bottom quintiles.

E.5 Longitudinal Analysis of Migrants

Table A-17 shows that the timing of the relationship between migration and medical spending lends further support to our interpretation that migration has a causal effect on medical spending. The table shows the difference in medical spending between migrants to richer areas and migrants to poorer areas. At baseline, before migration, total medical spending is statistically indistinguishable for both groups, but the period after and two periods after migration, it is about $2000 to $3000 higher for the group that moved to a richer area. This

Table A-16: Effect of Zip Code Income Quintiles and Education on Total Medicare Expenditures.

	(1)	(2)	(3)
2nd Zip Code Income Quintile	83.0		215.5
	(192)		(190)
3rd Zip Code Income Quintile	-300.3		-85.9
	(189)		(189)
4th Zip Code Income Quintile	72.0		373.5 **
	(194)		(195)
Top Zip Code Income Quintile	-157.4		318.9 *
	(192)		(195)
Attended High School		-63.9	-45.1
		(223)	(231)
High School Graduate		-843.7 **	-923.0 **
		(171)	(179)
Attended College		-1288.2 **	-1337.1 **
		(203)	(213)
College Graduate		-1455.8 **	-1593.1 **
		(207)	(221)
Fixed-Effects	age categories (65-74, 75-84, 85+), year, and sex		
R-Squared	0.04	0.03	0.03
Observations	76304	77547	73506

Source: MCBS, 1992-99.

Notes: Data are for total (Parts A+B) Medicare expenditures, adjusted for regional price variation using the GPCI and the hospital wage-price indices.

Table A-17: Migration and the Evolution of Medical Spending Among the Elderly.

	Annual Total Medical Spending		
	At Time t-1	At Time t	At Time t+1
Moved to a Poorer Area between time t-1 and t	Reference Group	Reference Group	Reference Group
Moved to a Richer Area between time t-1 and t	965.5	**2268.1**	**2880.8**
	(1066)	(1058)	(1505)
R-squared	0.01	0.01	0.01
Unique individuals	1870	1870	948
Person-years	1990	1990	977

Notes: Robust standard errors clustered by individual appear below coefficients. Coefficients in bold are significant at the 95% level.

Table A-18: Changes in health and migration patterns among the non-institutionalized Elderly.

Multinomial Logit Outcome:	Moved to richer zip code between t and t+1	Did not move	Moved to poorer zip code between t and t+1
# ADL limitations decreased between t-1 and t	Reference Group		Reference Group
# ADL limitations constant between t-1 and t	-0.00530 (0.00285) p=0.063	Reference Outcome	-0.00604 (0.00252) p=0.017
# ADL limitations increased between t-1 and t	0.00288 (0.00320) p=0.369		-0.00209 (0.00312) p=0.503
Pseudo R-Squared		0.0048	
Observations		21181	

Notes: These are the results of a multinomial logit for the non-institutionalized population in the 1992-99 MCBS. The coefficients are marginal effects, with robust standard errors below in parentheses. Below these are p-values. Year fixed-effects are included.

is inconsistent with the reverse causality explanation, where health spending changes induce migration.

Finally, Table A-18 sheds some light on the characteristics of migrants. The table shows the results of a multinomial logit regression, with three outcomes: movement to a poorer (in per capita income terms) zip code, no movement, and movement to a richer zip code. The covariates are prior changes in Activities of Daily Living (ADL) limitations. The analysis reveals that people whose ADLs remained unchanged between time t-1 and t were less likely to move between t and t+1. It also shows that people whose ADLs rose were no more likely to move to richer or poorer areas than those whose ADLs fell. This casts further doubt on the possibility that migration is the outcome of a change in health and health spending, rather than the hypothesis that it causes changes in health spending. It also lends more support to the hypothesis that people in richer areas spend more simply because standards of care are higher there, and not necessarily because sick elderly people seek to move there.

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