Does Medicare Save Lives?

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Abstract

The health insurance characteristics of the population changes sharply at age 65 as most people become eligible for Medicare. But do these changes matter for health? We address this question using data on over 400,000 hospital admissions for people who are admitted through the emergency department for “non-deferrable” conditions—diagnoses with the same daily admission rates on weekends and weekdays. Among this subset of patients there is no discernable rise in the number of admissions at age 65, suggesting that the severity of illness is similar for patients on either side of the Medicare threshold. The insurance characteristics of the two groups are very different, however, with a large jump at 65 in the fraction who have Medicare as their primary insurer, and a reduction in the fraction with no coverage. These changes are associated with small but statistically significant increases in hospital list charges and in the number of procedures performed in hospital. We estimate a nearly 1 percentage point drop in 7-day mortality for patients at age 65, implying that Medicare eligibility reduces the death rate of this severely ill patient group by 20 percent. The mortality gap persists for at least nine months following the initial hospital admission.

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Medicare pays nearly one-fifth of total health care costs in the United States. Yet, evidence on the health effects of the program is limited. Studies of aggregate death rates before and after the introduction of Medicare show little indication of a program impact (Finkelstein and McKnight, 2005). The age profiles of mortality and self-reported health in the population as a whole are likewise remarkably smooth around the eligibility threshold at age 65 (Dow, 2004; Card, Dobkin and Maestas, 2004). While existing research has shown that the *utilization* of health care services increases once people become eligible for Medicare (e.g., Decker and Rapaport, 2002, McWilliams et al., 2003, Card, Dobkin and Maestas, 2004; McWilliams et al., 2007), the health impact of these additional services remains uncertain.

This paper presents new evidence on the health effects of Medicare, based on differences in mortality for severely ill people who are admitted to California hospitals just before and just after their 65th birthday. Specifically, we focus on unplanned admissions through the emergency department for "non-deferrable" conditions – those with similar weekend and weekday admission rates. Our sample includes admissions for conditions such as obstructive chronic bronchitis, acute myocardial infarction (AMI), and stroke, comprising 12% of hospital admissions for people between the ages of 60 and 70, and accounting for about 25% of all deaths between these ages. We argue that the decision to present at an emergency department is unlikely to depend on insurance status for patients with these conditions. Consistent with this assertion, the arrival rate is nearly identical for patients just under and just over age 65. In contrast, admission rates for all causes jump 7% once people reach 65, and even total emergency department admissions rise by 3%.

Focusing on non-deferrable admissions, we turn to an analysis of the age profiles of patient characteristics and outcomes, testing for discontinuities at age 65. The demographic composition and comorbidities of the sample trend smoothly through the age 65 barrier, as would be expected under the assumption of no differential sample selection pre- and post-Medicare eligibility. On the other hand, the fraction of patients with Medicare as their primary insurer rises by about 50 percentage points, while the fraction with no insurance drops by 8 percentage points

Associated with these changes in insurance we find a small but statistically significant increase in the number of procedures performed in the hospital, and a 3% rise in total list charges. Using death records matched to our sample of hospital admissions, we find a clearly discernable drop in mortality once people become eligible for Medicare. Relative to people who are just under 65 when admitted, those who are just over 65 have about a 1 percentage point lower likelihood of death within a week of admission, or roughly a 20 percent reduction in 7-day mortality. A similar absolute reduction in mortality is registered at longer horizons and persists for at least nine months, suggesting that the differential treatment afforded to those with Medicare coverage has an important impact on patient survival.

We conclude by discussing potential channels for the Medicare effect. One mechanism is an increase in services for the relatively small fraction (<10%) of patients who move from uninsured to insured status at age 65. While previous studies have found evidence of this shift, our estimated mortality effects are too large to be driven entirely by gains for such a small group.[1] The switch to Medicare coverage at 65 could also lead to increased treatments for

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[1] Canto et al. (2000) and Hiestand et al. (2004) find that self-paying (i.e., uninsured) patients with acute myocardial infarction (AMI) -- one of the largest diagnoses in our sample of non-deferrable conditions – are less likely to receive invasive treatments than those with insurance.

patients who were previously covered by private insurance or Medicaid.[2] Though we see modest rises in treatment intensity at age 65, it is unclear whether these changes account for the reduction in mortality, or whether other factors (such as changes in the timeliness of treatment) also play some role.

The next section presents a brief overview of the Medicare program and existing research on its impacts. Section III outlines our regression-discontinuity research design. Section IV describes our procedure for identifying non-deferrable emergency department admissions, and summarizes our tests for differential selectivity between patients just under and just over 65. Section V presents our main analysis of the age profiles of treatment intensity and mortality for the sub-sample of non-deferrable admissions. Section VI discusses potential channels for the Medicare effect on treatment intensity and heath. Section VII concludes.

II. Medicare: Background and Previous Studies

II.a. Medicare Eligibility and Health Insurance

Medicare coverage is available to people who are 65 or older and have worked at least 10 years in covered employment.[3] Medicare is also provided to people under 65 who are receiving Social Security Disability Insurance (DI): currently about 12% of the population is already on the program by the time they reach 65.[4] Age-eligible individuals can enroll on the first day of the

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[2] In Card, Dobkin, Maestas (2008) we show that there are large increases (10-20%) in rates of coronary bypass surgery, cholecystectomy (gall bladder removal) and many other procedures at age 65. We argue there that the pattern of effects is consistent with less restrictions in Medicare than in many private insurance plans.

[3] Spouses of people who qualify are also qualified. U.S. citizens and legal aliens with at least five years of residency can also enroll in Medicare at age 65 by paying monthly premiums

[4] See Autor and Duggan (2003) for a recent analysis of trends in DI. A very small number of people who need kidney dialysis are also eligible.

month that they turn 65 and obtain Medicare hospital insurance (Part A) for free. Medicare Part B, which covers doctor bills and some other charges, is available for a modest monthly premium.

The onset of Medicare eligibility leads to sharp changes in health insurance status at age 65. These changes are illustrated in Figure 1, which presents data from the 1999-2003 National Health Interview Surveys (NHIS) on four different dimensions of insurance coverage: Medicare coverage; any insurance coverage; coverage by multiple policies; and having primary insurance coverage in a managed care policy. The figure shows the means of each outcome by age (measured in quarters), as well as the fitted age profiles from a simple regression that includes a quadratic in age, a dummy for age over 65, and interactions of the dummy with age and age-squared.

The data show a 60 percentage point rise in Medicare coverage at age 65, from 12% to just over 70%. In fact, the jump is probably even larger: a recent study by Cohen and Martinez (2007) analyzes the responses to a probe question added to the 2005 and later NHIS surveys and concludes that Medicare coverage for people over 65 is under-reported by roughly 8 percentage points in the basic NHIS.[5] Associated with the onset of Medicare eligibility at 65 is an increase of about 9 percentage points in the fraction of people with any coverage, leaving only about 3 percent of the population over 65 uninsured, compared with about 13% of those under 65.[6]

The two other insurance characteristics shown in Figure 1 also change sharply at 65. The fraction of the population covered by multiple policies rises by about 45 percentage points, as many of those with private insurance before 65 obtain a supplemental policy to "top up" their

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[5] Unfortunately the probe is only asked of people over 65, so there is no way to know the degree of under-reporting of Medicare coverage among people less than 65. Recent data from the Current Population Survey, which includes a series of insurance questions, suggest that the Medicare coverage rate rises from 17 to 85 percent between ages 64 and 65.

Medicare coverage.[7] Conversely, the fraction of people covered by managed care in their primary policy falls by 30 percentage points. This drop reflects the relatively high rate of managed care coverage in the pre-65 insurance market, coupled with the relatively low fraction of Medicare recipients who chose managed care over traditional fee-for-service insurance in the period up to 2002.[8]

Overall, the data in Figure 1 show striking changes in the heath insurance coverage of the population at age 65. Within a few weeks of becoming eligible for Medicare, at least 80% of the population is enrolled in the program. In the process, about ¾ of those who were previously uninsured obtain coverage. Many Medicare enrollees who were previously covered by a private plan enroll in a supplemental policy, creating a sharp rise in the incidence of multiple-coverage. And, since most Medicare recipients choose traditional fee-for-service coverage, the fraction of the population with managed care is reduced by half.

II.b. Impacts of Medicare

Existing research has shown that the onset of Medicare age-eligibility leads to an increase in the use of health services. Two early studies focus on changes in the use of medical screening procedures by people who were less likely to have health insurance prior to 65. Decker and Rapaport (2002) find a relative increase in mammogram screenings by less-educated and black women after 65. McWilliams et al. (2003) find that medical screenings increase more for people who lacked insurance coverage in the two years before reaching age 65. A study by Dow (2004)

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[6] The probe questions in the 2005 NHIS suggest that overall coverage after age 65 is under-estimated in the NHIS by 2-3 percentage points (Cohen and Martinez, 2007, Table 3).

[7] Medicare Parts A and B include significant deductibles and require a co-insurance payment of 20% on many bills. Some individuals obtain supplementary coverage through a previous employer, while others purchase a private "Medigap" policy or enroll in a Medicare managed care plan.

[8] In our NHIS sample about 85% of Medicare recipients are enrolled in traditional fee-for-service Medicare. Prior to 2003 the only managed care option in Medicare was to enroll in a Medicare HMO plan.

compares changes in hospitalization rates from 1963 (3 years before the introduction of Medicare) to 1970 (4 years after) for different age groups and finds a relative rise among those 65 and older. Card, Dobkin, and Maestas (2008) examine the age profiles of hospital admissions in California, Florida, and New York, and find large increases in hospitalization rates at age 65, particularly for elective procedures like coronary bypass surgery (16% increase in admission rates), and hip and knee replacement (23% increase). McWilliams et al. (2007) find that hospitalizations and doctor visits rise among previously uninsured individuals with hypertension, heart disease, diabetes, or stroke diagnosed before age 65.

As is true for health insurance more generally (see Levy and Meltzer, 2004), it has proven more difficult to identify the health impacts of Medicare.[9] Most existing studies have focused on mortality as an indicator of health.[10] An early study by Lichtenberg (2001) used Social Security Administration (SSA) life table data to test for a trend-break in the age profile of mortality at age 65. Although Lichtenberg identified a break, subsequent analysis by Dow (2004) showed that this is an artifact of the interval smoothing procedure used to construct the SSA life tables. Comparisons based on unsmoothed data show no evidence of a shift at age 65 (Card, Dobkin, Maestas, 2004). Finkelstein and McKnight (2005) explore trends in state-specific mortality rates for people over 65 relative to those under 65, testing for a break around 1966 – the year Medicare was introduced. They also examine the correlation between changes in relative mortality after 1966 and the fraction of elderly people in a region who were uninsured in

[9] Currie and Gruber (1996a, 1996b) find that Medicaid insurance for low-income pregnant women leads to improvements in health of newborns and a reduction in infant mortality.

[10] An exception is Card, Dobkin, and Maestas (2004), where we look at age profiles of self-reported health status. These are relatively smooth around age 65. Decker (2002) examines the outcomes of breast cancer patients pre- and post Medicare eligibility and finds some evidence of better outcomes for those over 65.

1963. Neither exercise suggests that the introduction of Medicare reduced the relative mortality of people over 65, though it should be noted that the power of these analyses is limited.

III. A Regression Discontinuity Analysis of Health Outcomes

Like earlier studies, we use comparisons around the age threshold for Medicare eligibility to measure the health impacts of the program. Unlike most existing studies, however, we attempt to isolate a sub-population whose immediate mortality experience is more likely to be affected by differences in health care services provided to people once they are eligible for Medicare. Specifically, we focus on people who are admitted to the hospital through the emergency department for relatively severe illnesses. Any extra services (or improvement in the quality of services) offered to this sub-population have at least a plausible chance of affecting short run mortality. By comparison, Medicare-related changes in health care would have to have a very large impact on mortality to generate a detectable effect on the overall population.[11]

Our analysis is based on a reduced form regression-discontinuity (RD) model of the form:

(1) $y_i = f(a_i, \alpha) + Post65_i\, \beta + \varepsilon_i$

where y_i represents a health-related outcome for patient i, a_i represents the patient's age (measured in days from his or her 65th birthday), $f(\cdot)$ is a function that is continuous at age 65 with parameter vector α (e.g., a flexible polynomial), $Post65_i$ is an indicator for whether the patient has passed his or her 65th birthday, and ε_i is an error term reflecting the influence of all

[11] For example, in a randomized trial in which Medicare were made available to a treatment group of 65 year olds and withheld from the controls, the program would have to have a 7% impact on annual mortality to yield a t-statistic of 2 or higher on the difference in one-year mortality between the treatment and control groups, even with 100,000 observations in each group. The reason is that the baseline mortality rate of 65 year olds is only about 1.5% per year.

other factors. In all specifications, we also interact the age polynomial with the $Post65_i$ indicator to allow the slope of the age profile to vary on either side of the age 65 threshold. If y_i is a measure of health care services provided to patient i, then we interpret β as a scaled estimate of the causal effect of Medicare coverage on the provision of services. As in other "fuzzy" RD designs (Hahn, Todd, and van de Klauuw, 2001), the scale factor is just the difference in the probability of treatment on either side of the threshold, although in the case of Medicare, the treatment is potentially multi-dimensional (see section VI, below).[12] If y_i is an indicator for mortality over some time horizon, then we interpret β as a scaled estimate of the causal effect of Medicare coverage on the likelihood of death in that time interval.

We defer a detailed discussion of the possible channels leading to the reduced form impact of Medicare coverage on health care services to Section VI. For now, we note that the data in Figure 1 suggest at least three alternatives: (1) an effect attributable to the increase in the overall fraction of the population with any health insurance; (2) an effect driven by people switching from an insurance carrier other than Medicare to a package that includes Medicare;[13] (3) an effect attributable to the change from managed care coverage to indemnity insurance. For example, hospitals may provide extra services if they know a patient is covered by Medicare and supplemental insurance, rather than being uninsured, or covered by a typical pre-65 policy. Alternatively, there may be a reduction in the delay in verifying insurance status for Medicare patients, or in receiving approval for certain procedures that are limited by managed care providers.

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[12] See Imbens and Lemieux (2007) for an overview of recent work on regression-discontinuity methods. The causal effect is only identified for the subset of people whose status is changed at age 65.

[13] Arguably, one could break out this effect into an effect associated with Medicare coverage per se, and an effect associated with coverage by multiple policies.

As emphasized by Lee (2008), the key assumption underlying an RD analysis is that assignment to either side of the discontinuity threshold (in our context, to being observed just a few weeks older or younger than 65) is as good as random. In the context of equation (1) this requires that

(2) $E[\, \varepsilon_i \mid 65-\delta < a_i < 65] = E[\, \varepsilon_i \mid 65 \leq a_i < 65+\delta\,]$ for δ sufficiently small ,

which ensures that a simple comparison of the mean of y_i on either side of the age 65 threshold yields a consistent estimate of the parameter β.

In a sample of hospital admittees the assumption that patients close to age 65 are "as good as randomly assigned" to either side of the age threshold may fail if insurance status affects the probability a patient is admitted to the hospital. Since previous work has found that the onset of Medicare eligibility leads to an increase in hospitalization rates (Card, Dobkin, and Maestas, 2008) this is a serious threat to an RD analysis of the health outcomes of patients. Figure 2 illustrates the difficulty in using counts of hospital admissions based on California discharge records from 1992 to 2002. (The sample is described more precisely below). At age 65 the number of non-emergency department admissions jumps by approximately 12%, while the number of emergency department admissions rises by 3%. Assuming that the additional patients are not as sick as those who would enter the hospital regardless of Medicare eligibility, the average health of patients rises discretely at age 65.

In this paper we attempt to solve the sample selection problem by focusing on a subset of patients who are admitted through the emergency department (ED) for a relatively severe set of conditions that require immediate hospitalization. Specifically, we identify a set of admission diagnosis codes with similar ED admission rates on weekdays and weekends.[14] We then test the assumption that there is no remaining selection bias associated with the age 65 boundary by looking for discontinuities in the number of admissions at 65 and the characteristics of patients on either side of the boundary. Importantly, our procedure for identifying an unselected sample is unrelated to the age of patients. Thus, our tests for selection bias are unaffected by "pre-test bias," and provide a reasonable degree of confidence in the validity of our inferences.

As a check on inferences from this sample, we also use a simple bounding procedure (Horowitz and Manski, 1995) to estimate a lower bound (in magnitude) for the impact of Medicare eligibility on other patient samples, including the overall population of hospital admissions. This bound is fairly tight because the relative size of the group of "extra" patients who only enter the hospital if they are over 65 is modest (at most 12%) and because the gap between actual mortality experience of all patients and the "worst case" bound for the extra patient group is small. For example, the average 28-day mortality rate of all people admitted to the hospital who are just over 65 is 4.6%, whereas the lower bound on the mortality of the extra patients is 0. As we discuss below, this means that the "worst case" bias created by the selective inflow of patients after 65 is −0.3 percent – a relatively small bias.

Even if there is no differential selection around the discontinuity threshold, inferences from an RD design can be compromised if there are other factors that change at the threshold. One concern is retirement: 65 is a traditional retirement age, and studies have shown that health is affected by employment status (Ruhm, 2000). Nevertheless, we believe the confounding effect of retirement is relatively minor. First, as shown in Figure A in the online appendix,

[14] Hospital admissions are typically much lower on weekends than weekdays, in part because of staffing constraints. Dobkin (2003) shows that mortality rates for patients admitted on the weekend for diagnoses with a constant daily admission rate are the same as for patients admitted during the week.

recent data show no discontinuity in the likelihood of working at exactly age 65.[15] Second, the admission diagnoses included in our non-deferrable sample are relatively severe, and would normally preclude an immediate return to work. But the mortality gap we observe in this sample at age 65 emerges within 7 days of initial admission to the hospital, and thus is unlikely to reflect differences in survival between people who return to work and those who do not.

Another concern with the age 65 threshold is that recommended medical practices may change at this age. Until recently, for example, U.S. government agencies recommended different influenza vaccination policies for people over and under 65 (Smith et al, 2006). Again, however, we think this is unlikely to affect the characteristics or treatment of patients admitted through the ED for non-deferrable conditions.

IV. Sample Construction and Validation

Our sample is drawn from the universe of records for patients discharged from hospitals regulated by the State of California between January 1, 1992 and December 31, 2002. To be included in the sample, patients must have been admitted; thus, those who were sent home after treatment in the emergency department or who died either en route or in the emergency department do not appear in the sample.[16] As explained in the Data Appendix (included in the online appendix to this paper), we drop discharge records for patients admitted before January 1, 1992, or on or after December 1, 2002, to avoid length-biased sampling problems.

[15] This figure shows employment rates by quarter of age, using data from the 1992-2003 National Health Interview Surveys. The spike in retirement at age 65 has largely disappeared in the past two decades (von Wachter, 2002), reflecting the elimination of mandatory retirement and the availability of Social Security benefits at age 62.

[16] According to a national survey of hospitals conducted by the General Accounting Office (2003), approximately 15% of the patients seen in an emergency department are admitted to the hospital.

The discharge dataset includes basic patient information (month of discharge, age in days at the time of discharge, gender, race/ethnicity, and zip code of residence) as well as medical information, including the principal cause of admission,[17] whether the admission was planned or unplanned, the route into the hospital (ED versus non-ED), the patient's primary health insurance provider, the length of stay, and a list of all procedures performed in the hospital. It also includes a scrambled version of the patient's Social Security Number, which can be used to track patients who are transferred or re-admitted, and to link mortality records. The Data Appendix describes our procedures for consolidating the records for patients who were transferred to new units in the same hospital, or to another hospital. It also describes the linked discharge-mortality file prepared for us by the California Department of Health Services that we merge with the initial discharge file in order to determine the date of death for patients in the sample.

One limitation of the discharge data is that approximately 5% of 64-year old patients in our sample have a missing SSN, compared with about 4% of those just over 65. Given that the in-hospital mortality rate of 60-64 year-old patients with a missing SSN is much higher than that of patients with a valid SSN (10.4% v. 6.3%), we believe that the ability to match longer-term mortality outcomes for 1/5th of this group once they reach 65 will tend to bias down any observed mortality improvements at 65. In any case, in Section V.e., we present evidence showing that the mortality effects we estimate are unlikely to have arisen mechanically as a result of merging procedures or selectively missing data.

As discussed in the previous Section, a critical step in our analysis is to select a subset of patients whose admission to the hospital is independent of insurance status. We do this by identifying a set of admission diagnosis codes (classified by 5-digit ICD-9) that have similar

[17] This is defined as "the condition established, after study, to be the chief cause of the admission of the patient."

admission rates through the ED on weekdays and weekends. For example, if admission for a given diagnosis code were equally likely on a weekend as on a weekday, then weekend admissions should constitute 2/7=0.29 of total admissions for that diagnosis. We compute the fraction of weekend admissions for all ICD-9 codes and limit our analysis sample to those codes for which the t-statistic for a test that the fraction of weekend admissions=2/7 is less than 0.965. Figure B in the online appendix shows how the distribution of the fraction of weekend admits over the diagnosis codes in our sample centers tightly around 2/7, in contrast to the distributions over all diagnosis codes and those associated with ED admissions (which center around a lower fraction of weekend admits). Arguably, these diagnoses are "non-deferrable," and patients with these conditions will present at the ED at the same rate just before and just after their 65th birthday, irrespective of Medicare coverage.

Table 1 summarizes the 10 most common diagnosis codes in this subsample of 425,315 "non-deferrable" admissions. The largest diagnosis category is obstructive chronic bronchitis with acute exacerbation. (This includes patients with chronic obstructive pulmonary disease – a common diagnosis for smokers and ex-smokers). Acute myocardial infarctions of all forms (i.e., including all 410.xx ICD-9 codes) represent the second most common group of admissions in our sample. The top 10 diagnoses also include respiratory failure and two forms of stroke (intracerebral hemorrhage and cerebral artery occlusion).

To test that patients' inclusion in the "non-deferrable" admissions subsample is independent of whether they are under or over 65, we conducted a regression discontinuity analysis of the count of admissions by age. This procedure is similar to the test of manipulation proposed by McCrary (2008), though we have a discrete running variable (age, measured in days) and we use a parametric rather than a non-parametric approach. Figure 3 shows the age profiles of the log of the daily admission count for four groups of ED admissions, based on the magnitude of the t-statistic for the test that the fraction of weekend admissions=2/7. The groups of admission diagnoses with t-statistics in the top two quartiles ($t>6.62$, and $2.54<t<6.62$) show clear evidence of a jump at age 65, whereas the age profile for diagnoses in our preferred group, with $|t| < 0.965$, shows no visible evidence of an increase in admissions.

Formal testing results are summarized in Table 2. Each pair of columns in this table presents the estimated discontinuities at age 65 from two alternative RD models for the log of the number of admissions by age (in days) of the admitted patient. We limit the sample to people between the ages of 60 and 70, resulting in 3,652 observations – one for each potential value of age in days. Both specifications include a dummy for age over 65 and a quadratic polynomial fully interacted with the post-65 dummy. We have also fit the models with cubic polynomials and found no significant differences in the estimated values of the post-65 effects (see Table A in the online appendix).

Although we know each patient's exact age (measured in days) at the time of admission, we do not know patients' birthdates or the exact admission date.[18] Since Medicare eligibility begins on the first day of the month that a person turns 65, people who are admitted in the period up to 31 days before reaching their 65th birthday may or may not be eligible for Medicare. Figure C in the online appendix shows the fraction of admitted patients in our non-deferrable sample who are recorded as having Medicare as their primary insurance provider, by age in days for a narrow window around age 65. This fraction is relatively flat for people up to a month before their 65th birthday, then rises linearly in the 31 days before reaching age 65, as would be expected given Medicare eligibility rules and a uniform distribution of birthdates.

Because we do not know the Medicare eligibility status of patients who are admitted within 31 days of their 65th birthday, the specifications reported in the even-numbered columns of Table 2 include a dummy for these observations. The addition of this dummy has relatively little impact on the estimated coefficients.[19] Looking at the models in columns 1-4, we estimate that non-ED and planned ED admissions rise by about 12% at 65, while unplanned ED admissions rise by 2.6%. The remaining columns report the results for the four quartiles of unplanned ED admissions shown in Figure 3. As suggested by the graph, the estimated models for our preferred subgroup of diagnoses (in columns 11 and 12) show no evidence of a rise in admissions at age 65.

Although the number of admissions in our non-deferrable sample trends smoothly at age 65, we also tested for a change in the health characteristics of admissions at age 65. Specifically, we constructed a Charlson comorbidity score from the secondary diagnoses listed on each discharge record.[20] Figure D in the online appendix shows the age profile in the Charlson comorbidity scores for the non-deferrable sample. There is no discernable evidence of a drop in the severity of comorbidities at age 65; in fact, formal RD analysis on the age profile indicates a small but statistically insignificant *increase* in severity (see Table B in the online appendix). If we interpret the rise as a true measure of the change in severity (and not a result of up-coding incentives in the Medicare payment system), it suggests that if anything our sample becomes slightly *less healthy* at age 65.

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[18] This restriction was imposed by the California Department of Health and Human Services as a condition for access to the discharge files.

[19] For all six models presented in the even-numbered columns of Table 2 the t-statistic for a test that the coefficient of the dummy is 0 is well below the usual critical value.

[20] We are grateful to a referee for suggesting this analysis. The Charlson comorbidity index is a weighted count of the presence of 19 diseases (e.g., diabetes with end organ damage is weighted 2, while peptic ulcer disease is weighted 1). We use the STATA coding for the index developed by Stagg (2006).

We have also checked for discontinuities in the case mix and demographic composition of the non-deferrable subsample at age 65. Counts of admissions for each primary diagnosis code included in our subsample trend smoothly with age, which suggests the case mix is very stable through the age 65 boundary. Tests for jumps in the racial composition, gender, and fraction of Saturday or Sunday admissions (available on request) are all far below conventional critical values. To increase the power to detect differences in patient health, we used all the available covariates for an admission (including age, race/ethnicity, gender, year, month, and day of admission, and principal diagnosis fixed effects) to fit linear probability models for mortality over 7, 14, 28, 90 and 365 days. We then took the predicted mortality rates from these models and conducted an RD analysis, looking for any evidence that the predictors of mortality shift at age 65. The age profiles of 7-day and 28-day predicted mortality are shown in Figure E of the online appendix. (Results for other follow-up periods are very similar). These age profiles are extremely smooth, and show no jump at age 65. In an RD specification with a quadratic in age and a dummy for over 65, interacted with the linear and quadratic terms, the t-statistics for the post-65 coefficient are 0.4 (7 day mortality) and 0.25 (28 day mortality), providing no evidence that the observable health of the sample changes at age 65.

A final piece of indirect evidence that patients with severe conditions are not more (or less) likely to present at the emergency department once they become Medicare-eligible comes from studies of the effect of cost-sharing (i.e., co-payments and deductibles) on the use of the ED.[21] In the RAND health insurance experiment, patients with cost-sharing insurance plans were no less likely to present at the ED for the most serious conditions (chest pain/acute heart disease, surgical abdominal disease, acute eye injuries, second degree burns) than those with the "free" plan (O'Grady, Manning, Newhouse, and Brook, 1985). Similarly, two recent studies of the introduction of cost-sharing for ED visits by patients in an HMO (Selby, Fireman, and Swain, 1996; Wharam, Landom, Galbraith et al., 2007) conclude that co-payments have no large or significant effect on ED visits for patients with severe conditions. The sample sizes in these studies are modest, however, and one certainly could not detect changes of the order of 3% in the use of the ED, which is the magnitude of the jump at age 65 for all unplanned ED admissions in the California discharge data. A fourth HMO-based study by Hsu, Price, Brand, Ray, Fireman, Newhouse, and Selby (2006) has much larger sample sizes and concludes that the introduction of modest co-payment requirements reduces ED visits. This study does not break down ED visits by the severity of patients' conditions, though the authors find that patients with co-payment requirements have somewhat better clinical outcomes, which suggests that patients with life-threatening conditions like AMI, stroke, and chronic obstructive pulmonary disease are obtaining appropriate medical services. Overall we interpret these studies as supporting the hypothesis that people with severe conditions present at the ED independent of their insurance status.

V. Shifts in Insurance, Health Services, and Mortality at 65

V.a. Insurance

We now turn to the impact of the Medicare eligibility age on health-related outcomes. We begin by looking at health insurance coverage. Figure 4 shows the age profiles of the fractions of people with various primary insurers (private, Medicaid, Medicare, other, and none) in the non-deferrable admissions subsample. Consistent with the patterns in Figure 1 for the overall population, we see a big increase in the fraction of patients with Medicare as their

[21] We are grateful to a referee for suggesting that we consider this literature.

primary insurer at 65, coupled with a decline in the fraction with no insurance. RD models for health insurance outcomes are presented in Table 3. The models follow the same specification as in Table 2, although we now include a set of covariates (year, month and day of admission, race/ethnicity, gender, and admission diagnosis fixed effects) in the specifications shown in even-numbered columns. For reference, the specifications in the odd-numbered columns exclude these controls and also exclude the dummy for admissions in the 31 days before a patient's 65th birthday.

The regression results confirm the visual impressions conveyed in Figure 4. At age 65, the fraction of patients with Medicare as their primary insurer rises by about 47 percentage points, while the fractions with private insurance and Medicaid both fall.[22] Note that in the sample of non-deferrable admissions the Medicare coverage rate at age 64 is 24%, substantially higher than in the overall population (shown in Figure 1). Presumably this reflects the fact that many of these patients are chronically ill and on DI prior to 65. The percentage with no insurance at 64 is correspondingly a little lower than in the overall population (10% versus about 13%), and the reduction in the rate of non-insurance at 65 is a little smaller (-8 percentage points in the nondeferrable subsample, versus -9.5 percentage points for the population as a whole). Nevertheless, as in the population as a whole, patients with non-deferrable conditions have much different insurance coverage just after age 65 than just before.

V.b. Intensity of Treatment

We have three basic measures of the intensity of treatment offered to patients: the length of their stay in hospital, the number of procedures performed, and total hospital list charges.[23] Figure 5 shows the age profiles for these measures, while Table 4 presents RD models similar to the specifications in Table 3. The age profile for mean length of stay is somewhat noisier than the other two profiles, but all three profiles suggest an upward jump at 65. The estimation results in Table 4 show that mean length of stay increases by 0.4 days (or about 4.5%) at 65, though the estimated gain is not statistically significant. Similarly, the number of procedures jumps by 0.1, or approximately 4% (with a t-ratio around 4), while log list charges jump by 2.5% (with a t-ratio of around 2.6).

One concern with an RD model for the logarithm of list charges is that the dispersion in charges may increase (or decrease) once patients become Medicare-eligible. If true, then the expected level of charges may rise by more (or less) than 3% at age 65 (see Manning, 1998, for a general discussion of modeling health spending). To evaluate this concern we fit RD models to the standard deviation of log list charges for patients in each age-at-admission cell (with age measured in days). These models showed no large or statistically significant effect on the dispersion in list charges at age 65. We also fit RD models to the 75th and 90th percentiles of list charges for each age-at-admission cell. These models showed that both the 75th and 90th

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[22] Unfortunately we have no information on secondary coverage. We suspect that many of the 45% who have private coverage prior to age 65 enroll in Medicare and a supplementary policy at 65.

[23] We sum the duration of stay, list charges, and number of procedures for all consecutive stays. List charges are accounting charges, and do not represent the charges actually billed to insurers or patients. They also exclude charges for physician services, and are not reported for patients at Kaiser hospitals (hence the smaller sample size in columns 5-6 in Table 4). We interpret list charges as a convenient "price-weighted" summary of services rendered, albeit at artificial prices. Note that if list prices are a markup over actual costs, then the percentage change in list charges will be a good indicator of the change in the costs of the services provided to patients who are just under or just over 65.

percentiles of list charges increase by about 2-3% at age 65. (The regression models, and associated graphs, are presented in the online appendix, Table C and Figures F and G).

Overall, we conclude that there are modestly sized but statistically significant increases in the intensity of treatment at age 65 for patients in our non-deferrable admissions sample, on the order of 3 percent. These increases are much smaller than the 10-25% increases in rates of elective procedures such as hip and knee replacements observed in the overall population (Card, Dobkin, and Maestas, 2008) but suggest that the availability of Medicare affects the utilization of health care services even for severely ill patients.

We also performed a more detailed analysis of the changes in the use of specific procedures at age 65 for two major sets of diagnoses: obstructive chronic bronchitis with acute exacerbation (the largest ICD-9 in our non-deferrable sample, shown in row 1 of Table 1); and acute myocardial infarction (AMI), which combines the various detailed AMI diagnoses in our non-deferrable sample. The results are summarized in Table D of the online appendix. For AMI admissions we see a relatively large and precisely estimated increase in the overall number of procedures at age 65 (a rise of 0.44 on a base rate of 5.0 among 64 year-olds, or approximately 9%) and significant increases in the use of several important diagnostic procedures, including coronary arteriography, cardiac catheterization, and angiocardiography.[24] In contrast, for obstructive chronic bronchitis patients, we see no change in the overall number of procedures, and small increases or decreases in the incidence of specific procedures. This analysis suggests that the relatively small increase in the overall number of procedures for all admission diagnoses in Table 4 is masking larger increases for certain "procedure intensive" diagnoses, like AMI, and

[24] Cutler and McClellan (2001) have estimated that invasive diagnosis and treatment procedures as a whole (including catheterization, angioplasty, and bypass surgery) are cost-effective in the treatment of AMI. The

near constancy for other diagnoses. Unfortunately, the sample sizes for other diagnoses are too small to permit a more extensive investigation. We conclude, however, that the onset of Medicare eligibility is associated with an increase in the use of specific potentially life-saving procedures

V.c. Transfers and Readmissions

Patients who are initially admitted for acute care may be transferred (i.e., discharged and immediately re-admitted) to another care/treatment unit in the same hospital, to another hospital, or to non-hospital care (e.g., nursing homes).[25] Because our data are derived from hospital discharge records, we cannot measure transfers to stand-alone skilled nursing facilities or to other care options that may be substitutable with post-acute care in a hospital setting. Nevertheless, we find that within- and between-hospital transfer rates rise at age 65, with a particularly large rise in within-hospital transfers (25%) that appears to be driven by a jump in the transfer rate to skilled nursing facilities within the same hospital. We also find a marginally significant reduction in the probability that patients are re-admitted to a California hospital within 28 days after their initial admission (point estimate = -0.6 percentage point reduction on a base readmission rate of 17.0% for 64 year olds, t=1.70). Graphs and estimation results for transfers and readmissions are presented in the online appendix (Figures H, I and Table E).

V.d. Mortality

Figure 6 plots the age profiles for the probability of death within 7, 14, 28, 90, 180, and 365 days of admission to the hospital, while the first two rows of Table 5 present estimates from RD regression models corresponding to each of these outcomes. Inspection of Figure 6 shows

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efficacy of specific procedures is less clear: see e.g., McClellan, McNeil and Newhouse (1994) and Cutler, McClellan and Newhouse (1999)

[25] Note that to avoid double counting we have collapsed all consecutive hospital stays to a single record.

that each of the mortality measures shows a drop on the order of 1.0 percentage point at age 65. The regression estimates in Table 5 confirm this: we observe a reduction in 7-day mortality of about 0.7 to 1.0 percentage points which persists over the longer follow-up periods. The effect is relatively precisely measured in the shortest time intervals but has an increasing sampling error as the follow-up window is extended, yielding t-ratios of about 5 at 7 days, about 3 at 28 days, and around 1.8 at 365 days.

We have performed extensive robustness checks to ensure that the mortality results are not an artifact of a particular specification of the RD model. As shown in row 3 of Table 5, specifications with a cubic age polynomial yield estimates that are similar to the simpler quadratic models, though typically a little smaller, particularly for the 28-day follow-up window. (Figure J in the online appendix compares the fits of linear, quadratic, and cubic RD models for 28-day mortality). We also refit the models using logits (rather than linear probability specifications) and obtained essentially identical estimates of the change in the probability of death at age 65 (see Table F of the online appendix). Finally, we used local linear regression (LLR) models to obtain "non-parametric" estimates of the mortality rates for patients just under and just over 65 (Hahn, Todd, and van der Klaauw, 2001; Imbens and Lemieux, 2008). Row 4 of Table 5 presents LLR-based estimates using a triangular kernel and the rule-of-thumb bandwidth selection procedure suggested by Fan and Gjibels (1996). These are very similar to the parametric estimates using a quadratic polynomial but a little more precise. Figure K of the online appendix presents LLR-based estimates of the 28-day mortality rate for patients on each side of the age 65 boundary, using all possible bandwidths between 1 month and 5 years.[26] The estimated mortality rates for patients just under 65 and patients just over 65 stabilize once the bandwidth reaches about 1 year, centering on values close to the predicted values from our basic quadratic specification.

We used the specification from row 2 of Table 5 to fit parametric RD models for the probability of death in all possible follow-up windows between 1 day and 2 years. The resulting estimates of the jump in mortality at age 65 are plotted in Figure 7, along with the associated 95% confidence intervals. The data show a robust pattern of reductions in mortality for windows of up to nine months on the order of 0.8-1.0 percentage points, with somewhat smaller point estimates for windows of 1-2 years.

Our estimates of the mortality effect of Medicare eligibility are relatively large: they represent a 14-20% reduction in 7-day mortality, a 7-9% reduction in 28-day mortality, and a 2-4% reduction in 1-year mortality relative to death rates among 64 year olds with similar conditions at admission. The emergence of the effect within 7 days of admission suggests that the extra services or changes in the quality of services provided to Medicare-eligible patients have an immediate life-saving impact.

It is also worth noting that the mortality reductions estimated in Table 5 appear to reflect changes in the treatment of patients with Medicare <u>within the same hospital</u>, rather than patient sorting to higher-quality hospitals at 65. The fractions of patients with non-deferrable conditions entering different kinds of hospitals show only small changes at age 65. The largest change is a reduction of about 3 percentage points in the fraction entering county hospitals. Interestingly, the 28-day mortality rate for 63-64 year olds is actually *lower* at county hospitals (6.8%) than at non-profit (9.2%), for-profit (9.0%), or district hospitals (9.7%) in our data, so it is implausible

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[26]Here we follow the recommendation of Imbens and Lemieux (2008) and use a rectangular kernel for the local

that such a small shift in patients out of county hospitals could have much affect on average mortality.[27] Thus, it does not appear that Medicare reduces mortality by shifting patients to better hospitals.

V.e. Robustness of Mortality Estimates – A Bounding Approach

To further probe our estimated mortality effects we used a simple bounding procedure to obtain lower-bound estimates of the (absolute) mortality effect of Medicare eligibility on broader samples of hospital admissions, including the entire patient population. The basis of this procedure is the observation that in any sample of sick people close to age 65 there are two subgroups: one group (which we index with subscript 1) who enter the hospital regardless of whether they are Medicare eligible or not; and a second group (indexed by subscript 2) who will only enter the hospital if they are over 65. Let $\alpha \geq 0$ represent the sample fraction of the second group. We have argued that among people with non-deferrable conditions, $\alpha = 0$. In more general patient populations, however, $\alpha > 0$, and a comparison of mortality between patients just over and just under 65 contains a selectivity bias.

Let m_1 denote the mortality rate of the first group if they enter the hospital just before their 65th birthday and let m_1' denote the mortality rate if they enter after 65. The causal effect of Medicare eligibility for group 1 is $\Delta = m_1' - m_1$. The observed mortality rate of the patient population just over 65 is an average for groups 1 and 2:

$$\bar{m} = (1-\alpha)m_1' + \alpha m_2 = (1-\alpha)(m_1 + \Delta) + \alpha m_2 ,$$

where m_2 is the post-65 mortality rate of group 2. Using this expression it is easy to show that:

$$\bar{m} - m_1 = \Delta - \alpha/(1-\alpha) \times (\bar{m} - m_2) . \quad (3)$$

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linear regressions on each side.

Thus, the mortality differential between the post-65 patient population and the pre-65 patient population is equal to Δ, the causal effect of Medicare eligibility on group 1, plus a bias term:

$$Bias = -\ \alpha/(1-\alpha) \times (\ \bar{m} \ - m_2\ )\ ,$$

which depends on the fraction of group 2, and the deviation of their post-65 mortality rate from the average of groups 1 and 2. Since $m_2 > 0$, a lower bound on the absolute value of the bias caused by the presence of group 2 in the post-65 patient population is

(4) $\quad Worst\text{-}case\ Bias = -\alpha/(1-\alpha) \times \bar{m}$.

This bias tends to 0 as $\alpha \rightarrow 0$, and is proportional to $\bar{m}$.

Table 6 presents estimates of the various terms in equation (3) for the 28-day mortality rate of various patient populations, including all patients (column 1); those who enter the hospital via a route other than the emergency department, or for a planned hospitalization (which we call "elective" admissions, in column 2); those who enter via the ED for an unplanned hospitalization (column 3); and the four subgroups of the unplanned-ED group, based on admission diagnoses with different ranges of weekend versus weekday admissions (i.e., the four subgroups graphed in Figure 3) in columns 4-7. The first row of Table 6 presents the estimated RD in the log of the number of hospital admissions at age 65, which is an estimate of $\alpha/(1-\alpha)$.[28] Row 2 shows the estimated change in the mortality rate of patients at age 65 (i.e., the estimate of $\bar{m} - m_1$), obtained from an RD model with an interacted quadratic function of age fit to aggregated

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[27] To see that the effect of a small amount of sorting is negligible, note that even if (contrary to fact) the mortality rate at county hospitals were 50 percent larger than that of private hospitals, it could account for at most a negligible amount of the estimated mortality gain: 0.03*0.045=0.00135 percentage points.

[28] If α is the share of all potential patients who are only admitted after age 65, then the proportional increase in admissions at age 65 is $(1 - (1- \alpha))/(1-\alpha) = \alpha/(1-\alpha)$, so the RD in log admissions is an estimate of $\alpha/(1-\alpha)$.

mortality rates by age in days.[29] Row 3 shows an estimate of the constant in the mortality regression, which is our estimate of the mortality rate for people just under 65. (The implied estimate of $\bar{m}$ is therefore the sum of the entries in rows 2 and 3). Row 4 shows our estimate of the worst-case selectivity bias, based on equation (4), while row 5 shows our lower bound estimate of the effect of Medicare eligibility on the patient population, and row 6 shows an estimated sampling error for this bound. Finally, for reference, row 7 shows the fraction of patients in each subgroup.

Three key conclusions emerge from the table. First, the lower-bound estimate of the overall effect of Medicare on the 28 day death rate of the entire patient population is -0.13% (and only marginally significant). This is about one-tenth as large as our estimate of the effect on the non-deferrable admissions group, who represent 12% of the overall patient population. Second, for "elective" admissions (column 2), our point estimate of the lower bound mortality effect is actually positive (as it is for the top quartile of diagnoses with lowest weekend admission rates in column 5). For these admissions we cannot rule out that selection bias explains the entire (relatively small) drop in mortality we see after age 65. Even for the two middle quartiles of weekend/weekday admission codes the estimated lower bounds on the Medicare effect are small. Thus, virtually all of the (lower bound) mortality effect we observe for the overall patient sample is attributable to the reduction in mortality for the non-deferrable subgroup.

A third observation is that the unadjusted change in mortality at age 65 for the top quartile diagnosis group (column 4) is actually positive (+0.27%). This is reassuring in two

[29] To construct a standard error for our lower bound we need to construct a standard error for $\Delta + \alpha/(1-\alpha)\,\bar{m}$, where Δ is the estimated RD in mortality, $\alpha/(1-\alpha)$ is the estimated RD in log admissions, and $\bar{m}$ is the estimated mortality rate for those just over 65, which can be estimated as the constant in the mortality regression (assuming age is normalized to 0 at age 65) plus the value of the RD in mortality. Since we need the covariance between the

ways. First, it proves there is no mechanical data problem that is causing us to measure lower death rates for all patients over 65.[30] Second, the diagnoses in this quartile are relatively non-life-threatening. In particular, the 28-day mortality rate for 64- year-old patients in this group is only 2.7%, somewhat below the death rate for patients admitted on an elective basis. It would be surprising if Medicare eligibility had much effect on mortality for such a relatively healthy group, and the estimates imply that it does not.

VI. Discussion

Our empirical results point to a significant positive effect of Medicare eligibility on the intensity of treatment for acutely ill patients with non-deferrable conditions and a negative effect on patient mortality. In this section we discuss the possible channels for this effect. To aid in this discussion it is helpful to consider a simplified causal model in which Medicare eligibility affects insurance characteristics, insurance affects health care services, and health services affect mortality. Building on the analysis in Section II, suppose that patient i has a health insurance package with a vector of characteristics z_i, including whether i has any coverage, whether he or she has Medicare or some other form of primary coverage, and (possibly) other characteristics. Assume the age profile for z_i is generated by a model of the form:

$$(5) \qquad z_i = g(a_i, \gamma_z) + Post65_i\, \pi + \upsilon_{zi} ,$$

where g is a smooth function of age (a_i) with parameters γ_z, υ_{zi} is an error term that is mean-independent of the dummy $Post65_i$, and π represents the vector of discontinuities in insurance

estimated parameters from the mortality and admissions models, we fit the two RD's as seemingly unrelated regressions using grouped age cells, and use the delta method to construct the sampling error.

30 We believe that any such data problems are likely to bias the results in the opposite direction. In particular, because the in-hospital mortality rate of people without SSNs is higher, at worst we would add to the sample at 65

characteristics at age 65. Suppose that the quality-adjusted health care services delivered to patient i, (S_i) depend on age, an error term υ_{si}, and the characteristics of the insurance package:[31]

$$(6) \qquad S_i = h(a_i, \gamma_s) + \theta' z_i + \upsilon_{si} .$$

Finally, assume the likelihood of death of patient i (y_i=1) depends on age and on quality-adjusted health services:

$$(7) \qquad y_i = k(a_i, \gamma_s) + \lambda S_i + \upsilon_{yi} .$$

Equations (5), (6) and (7) yield reduced form models like equation (1), with a discontinuity in health care services at age 65 equal to

$$(8a) \qquad \beta_s = \theta' \pi ,$$

and a discontinuity in mortality equal to:

$$(8b) \qquad \beta_y = \lambda \theta' \pi .$$

In this simplified setup, each element of the insurance package represents a separate "channel" that contributes additively to the reduced form effects on services and mortality. For example, the kth element of z_i contributes $\theta_k \pi_k$ to the RD in services and $\lambda \theta_k \pi_k$ to the RD in mortality. Unfortuntately, we have no information on the individual components of θ, and only limited information on the vector π of insurance changes at age 65. For example, we do not observe secondary coverage, or whether the primary insurance is managed care. Nevertheless, it is possible to shed some light on the mortality effect associated with one key insurance characteristic: whether the patient has any insurance coverage or none.

In particular, note that the maximum contribution of the "any coverage" channel cannot exceed π_c (the jump in coverage at 65) times the average mortality rate of uninsured 64-year

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a small group with higher potential mortality, which would lead to a rise in the measured death rate for people over 65.

olds, because the extension of coverage to the previously uninsured group can only reduce their mortality rate to 0. The average 7-day mortality rate of uninsured patients who are just under 65 years of age in our nondeferrable admission subsample is 0.05, while π_c=0.08 (Table 3, column 8). Thus the maximum reduction in mortality attributable to the reduction in the number of people with no health insurance is 0.004 – about 40% of the 7-day mortality effect we estimate. This is an extreme bound because it is based on the assumption that <u>none</u> of the previously uninsured would die if they were covered. A more plausible bound is that insurance coverage reduces the death rate by no more than one-half: in this case the "any coverage" channel can explain at most 20% of the total mortality effect.

In principle we can gain some additional insight by comparing changes in health insurance, the intensity of treatment, and mortality for different subgroups of patients.[32] Unfortunately, the limited demographic variables in our discharge data make this a challenging exercise. Comparisons across race/ethnicity groups are uninformative, because the sample sizes for blacks (n=41,000) and Hispanics (n=66,280) are too small to obtain useful estimates. We also tried dividing patients into two groups based on the average fraction of 55-64 year-old patients from the same zip code who had no insurance coverage. Even here, we were unable to estimate systematic differences in the changes in treatment intensity or mortality outcomes at age 65 between residents from "low insurance" and "high insurance" zip codes. We do find significant increases in the numbers of procedures and significant reductions in mortality even

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[31] This equation simplifies health care services to a single dimension. In fact, changes in insurance can cause some types of services to rise and use of other services to fall (or stay constant).

[32] In particular, assume that π varies by subgroup, with a value of $\pi(g)$ for subgroup g. If the parameters λ and θ are constant across groups then the discontinuity in services for group g is $\theta'\pi(g)$ and the discontinuity in mortality is $\lambda \theta'\pi(g)$. By comparing the relative sizes of the discontinuities in insurance, treatment intensity, and mortality across subgroups it is possible to judge whether the data are consistent with a "1-channel" explanation.

for patients from the high-insurance zip codes, suggesting that an increase in insurance coverage per se is not the explanation for the impacts of Medicare.

An alternative explanation for the measured mortality effects is that for most people Medicare imposes fewer restrictions than private insurance or Medicaid, leading to more (and possibly higher-quality) services to patients over 65 than to those under 65.[33] Card, Dobkin, and Maestas (2008) find clear evidence of this mechanism for a wide range of <u>non-urgent</u> medical procedures, such as surgery to insert a stent in a blocked coronary artery (which rises by 11% at age 65 in California, Florida, and New York), hip and knee replacement surgery (which rises by 23%), and gall bladder removal surgery (which rises by 18%). In fact, Table 4 presents evidence of small increases (3-4%) in the number of procedures and in total list charges at age 65 for patients with non-deferrable conditions. Arguably, however, such small increases in the intensity of treatment are unlikely to generate a 1 percentage point reduction in mortality, though as we noted above, the increase in procedures for AMI cases – which may be more sensitive to medical intervention – is closer to 10%.[34] Thus, the precise mechanisms for the mortality effect remain unclear, though we believe the evidence points to a combination of channels.

VII. Summary and Conclusions

[33] This net effect is likely a mix of some people attaining more generous coverage and others receiving less generous coverage relative to their pre-65 insurance plan. Even if Medicare is more generous with respect to case review procedures it may be less generous on other dimensions, such as prescription drug coverage.

[34] At the suggestion of a referee we looked at differences in the magnitude of the changes in treatment intensity at age 65 for patients from California counties with relatively high rates of managed care among non-elderly patients, versus patients from counties with relatively low rates of managed care. Specifically, we used data from the 1998 Area Resource File to split counties in two groups, based on whether the fraction of non-Medicare patients in HMO's was under or over 44% (the HMO penetration rate of the median individual's county). A specification parallel to the RD model in column 6 of Table 4 yields an estimated jump in log list charges of 3.6% (standard error=1.8%) for counties with above median HMO penetration, and 2.4% (standard error=1.1%) for counties with below median HMO penetration. Models for the RD's in the number of procedures show the opposite pattern across the two groups of counties but the difference is not statistically significant.

A longstanding question in health economics is whether health insurance affects health. This question is particularly relevant for Medicare, the largest medical insurance program in the country, which provides nearly universal coverage to people once they turn 65. We focus on measuring the health effects of Medicare eligibility for a relatively sick population – specifically, people who are admitted to the hospital through the emergency department with diagnoses that have similar admission rates on weekdays and weekends. In contrast to elective hospitalizations, there is no jump in these "non-deferrable" hospital admissions at age 65. Moreover, the predicted mortality rate of admitted patients (based on demographics and admission diagnoses) trends smoothly. These findings suggest that the underlying health of patients admitted with non-deferrable conditions is very similar whether the patients are just under or just over 65.

In light of this conclusion, we use a regression discontinuity approach to measure the impacts of reaching age 65 on the intensity of treatment in the hospital, and on mortality for up to two years after the hospital admission. We find modest but statistically significant increases in measures of treatment intensity at age 65, including the number of procedures performed in the hospital and total list charges. Associated with these changes we find an important and large reduction in patient mortality at age 65. Medicare eligibility reduces 7-day mortality by about 0.8 to 1.0 percentage points, with similar sized and statistically significant reductions at windows of up to 9 months. We probe the robustness of these findings by using a bounding procedure to evaluate the lower-bound effect of Medicare eligibility on the entire hospital patient population. The bounds for the overall population are consistent with the magnitude of the effect we estimate for patients with non-deferrable conditions, providing further credence to our basic results.

The magnitude of the estimated mortality effect of Medicare eligibility is too large to be driven solely by changes among the 8% of the patient population who move from no health insurance coverage to Medicare when they reach 65. This is an important distinction between our analysis and existing studies that have attributed much larger mortality gains to insurance status in specialized populations such as auto accident victims (Doyle, 2005) and former Medi-Cal recipients (Lurie et al. 1984, 1986). Instead, our findings point to a more widespread effect of Medicare, including an impact on patients who were insured prior to 65. Given the relatively modest increases in the intensity of treatment we measure at age 65, however, we conclude that the actual mechanism for this effect is unclear.

An important limitation of our analysis is that it focuses on just one health outcome, albeit an important one. Certainly, Medicare might affect other dimensions of health and other patient populations, with effects that arise through channels other than hospitalizations (e.g., outpatient care and prescription drug use), and that persist over a longer time horizon than that supported by our research design. Nonetheless, our analysis illustrates an important lesson for future research. Any plausible effect of insurance on health status in the general population will likely be small and easily confounded by selection effects in observational settings. Indeed, the only randomized health insurance experiment ever mounted found insignificant impacts of insurance on the health status of the overall population (Newhouse et al., 1993). Further progress on this question will require research designs based on larger samples than those typically available for health services research along with particular attentiveness to the selection problem.

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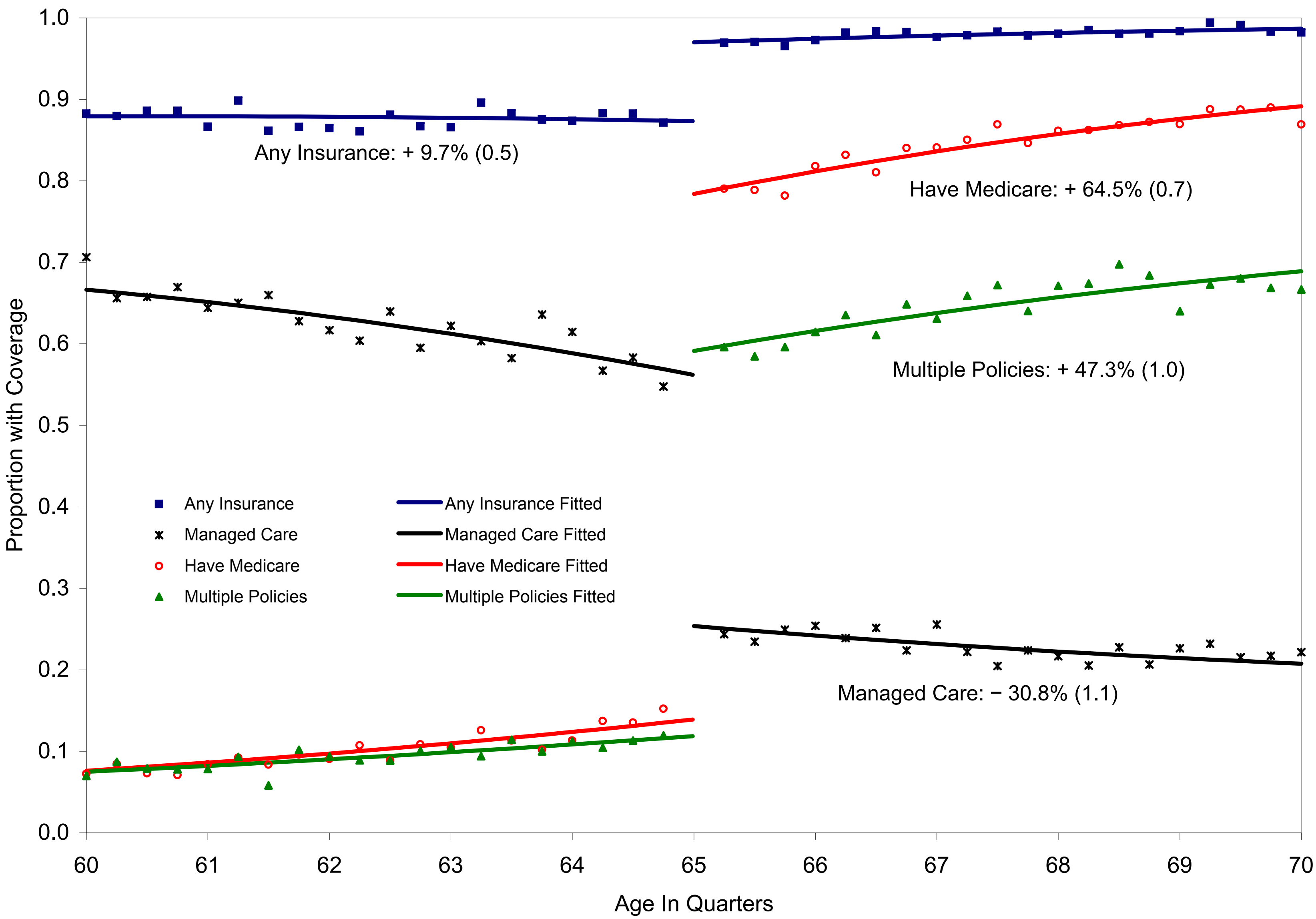
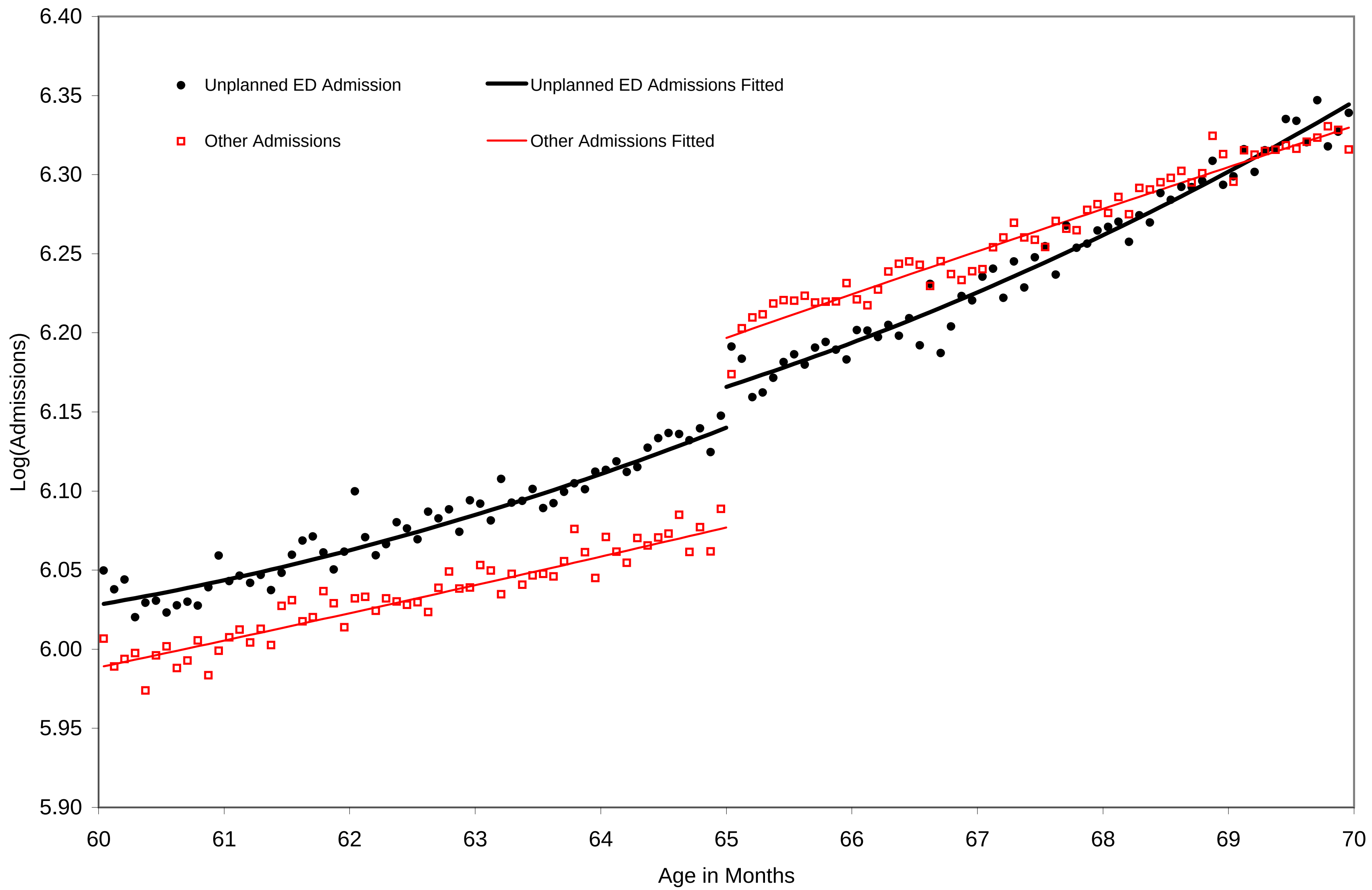
Figure 1: Changes in Health Insurance at Age 65 in National Health Interview Survey



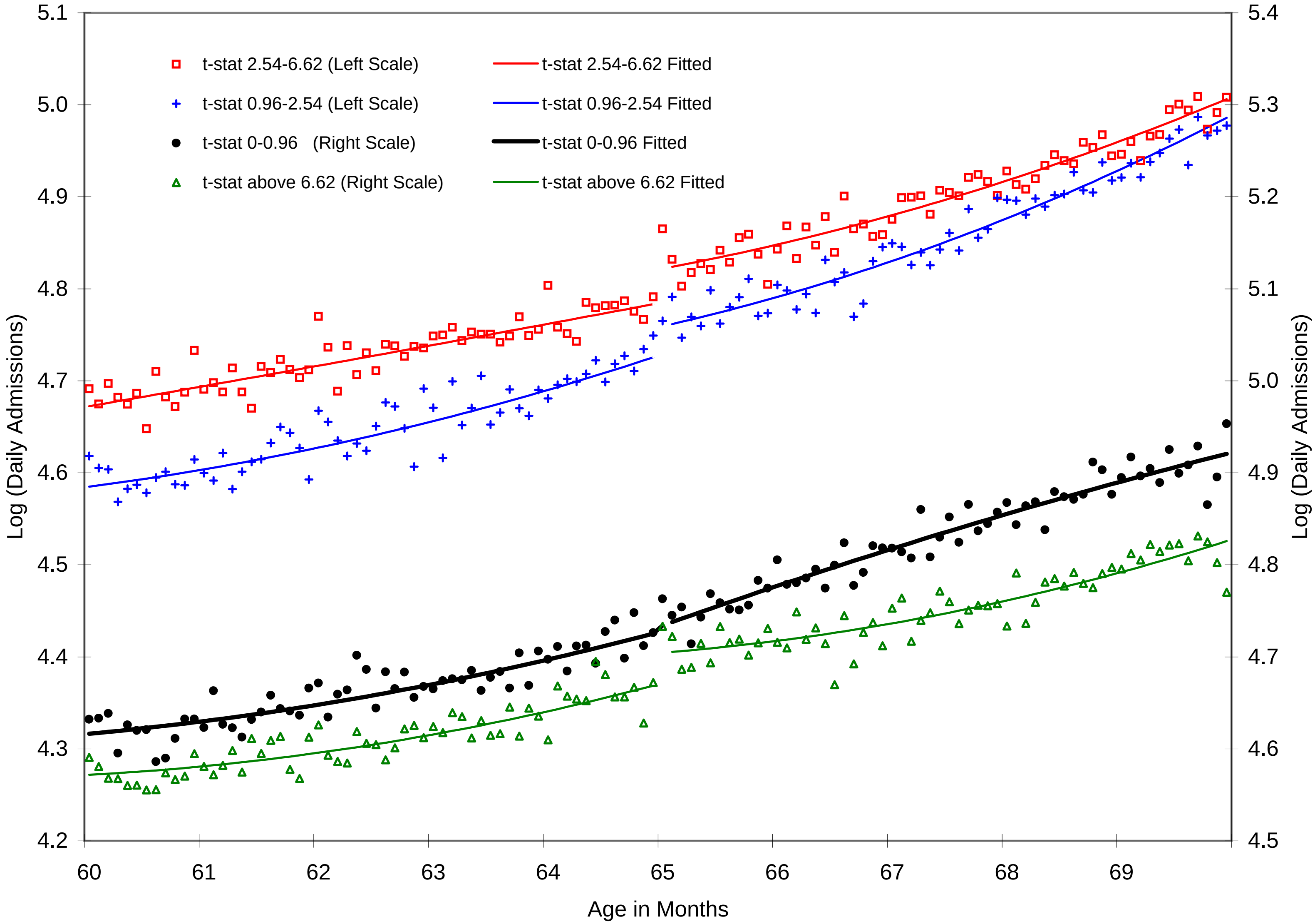
Notes: Samples are based on data from the National Health Interview Survey 1999-2003. The estimated discontinuities (and standard errors) at age 65 and the fitted lines are from a regression with a quadratic polynomial in age fully interacted with a dummy for age greater than or equal to 65. Models also include a dummy for people assigned to age 65.0 whose Medicare eligibility status is uncertain. Points represent means for people in each age cell (measured in quarters). Points for peope age 65.0 are not shown in Figure.

Figure 2: Number of Admissions by Route into Hospital, California 1992-2002



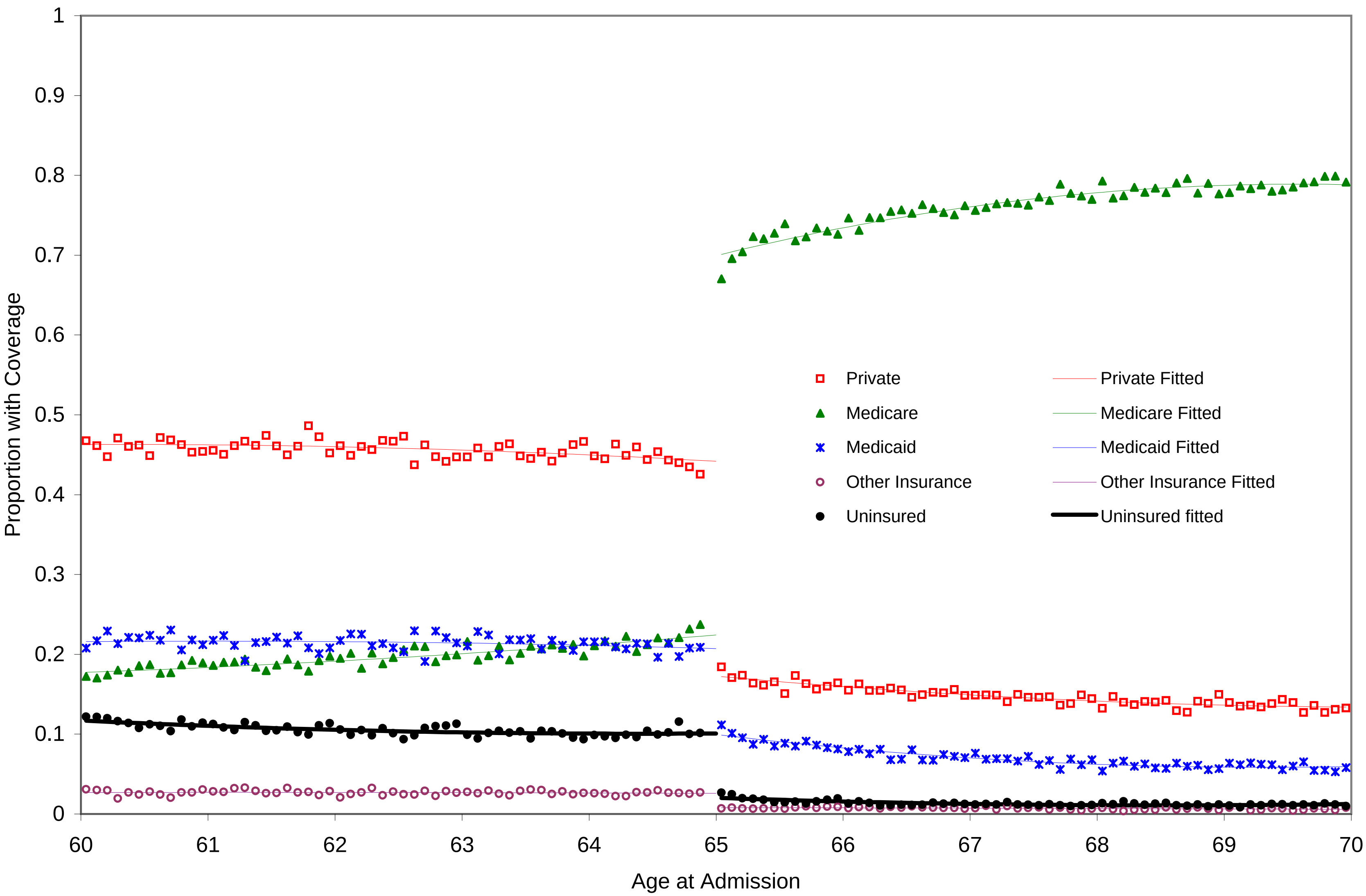
Notes: The lines are fitted values from regressions that include a second order polynomial in age fully interacted with a dummy for age >= 65 and a dummy variable for the month before people turn 65. The dependent variable is the log of the number of admissions by patient's age (in days) at admission, for patients between 60 and 70 years of age. The count of admissions is based on Hospital Discharge Records for California, and includes admissions from January 1, 1992 to November 30, 2002. The points represent means of the dependent variable for 30 day cells. The age profile for "Unplanned ED Admissions" includes admissions that occurred through the emergency department and were unplanned. The category "Other Admissions" includes all other admissions.

Figure 3: Admissions through the ED by Quartile of t-test for Weekend Proportion=2/7



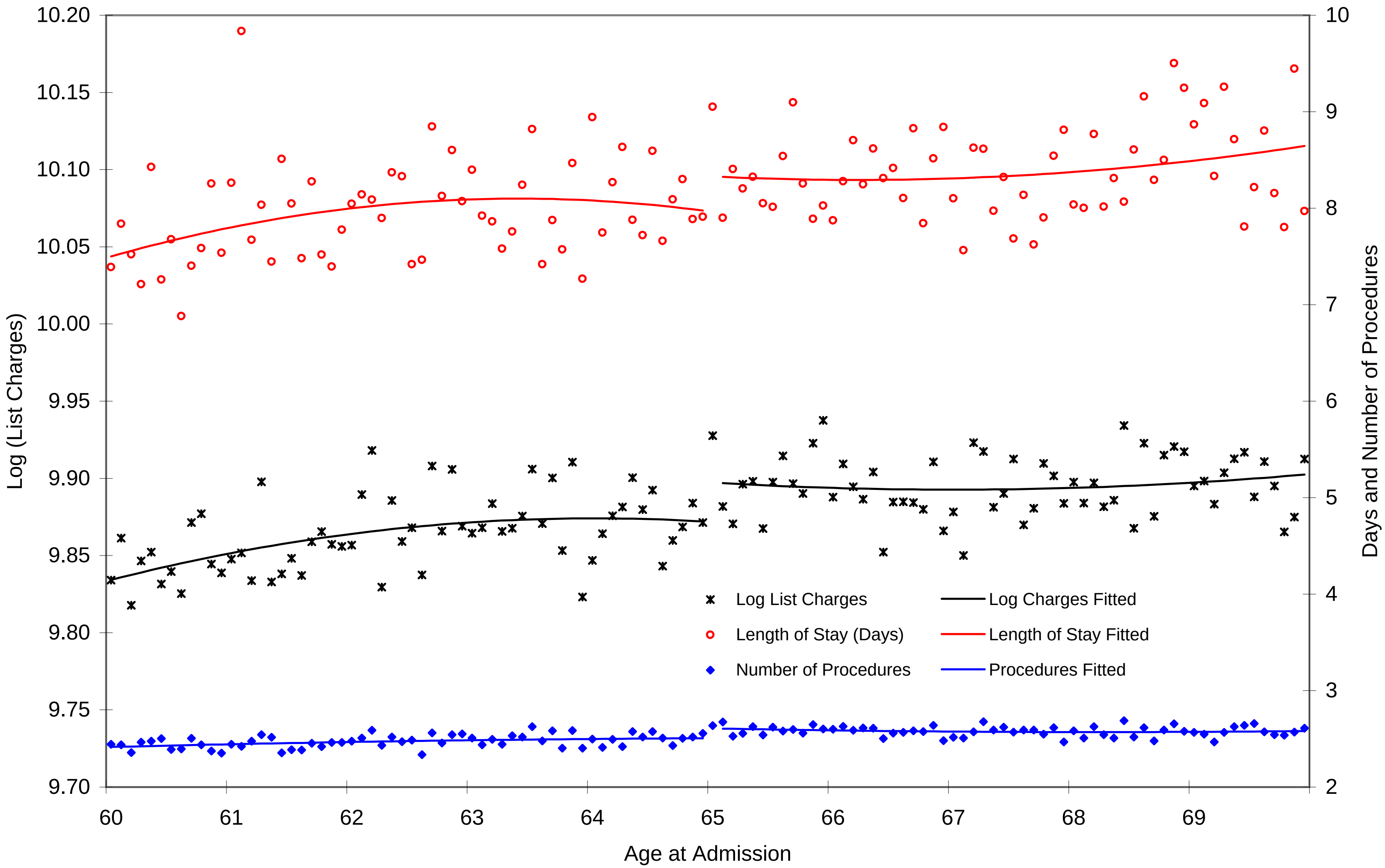
Notes: See notes for Figure 2. In this figure the population of patients with an unplanned admission through the ED is split into four groups based on the primary diagnosis ICD-9 code. Groups are defined by the range of the t-statistic for the test that 2/7 of admissions with the diagnosis occur on the weekend. The y-axis is the log of the number of admissions in the group by patient's age (in days) at admission, for patients between 60 and 70 years of age. The count of admissions is based on Hospital Discharge Records for California, and includes admissions from January 1, 1992 to November 30, 2002.

Figure 4: Primary Insurance Coverage of Admitted Patients



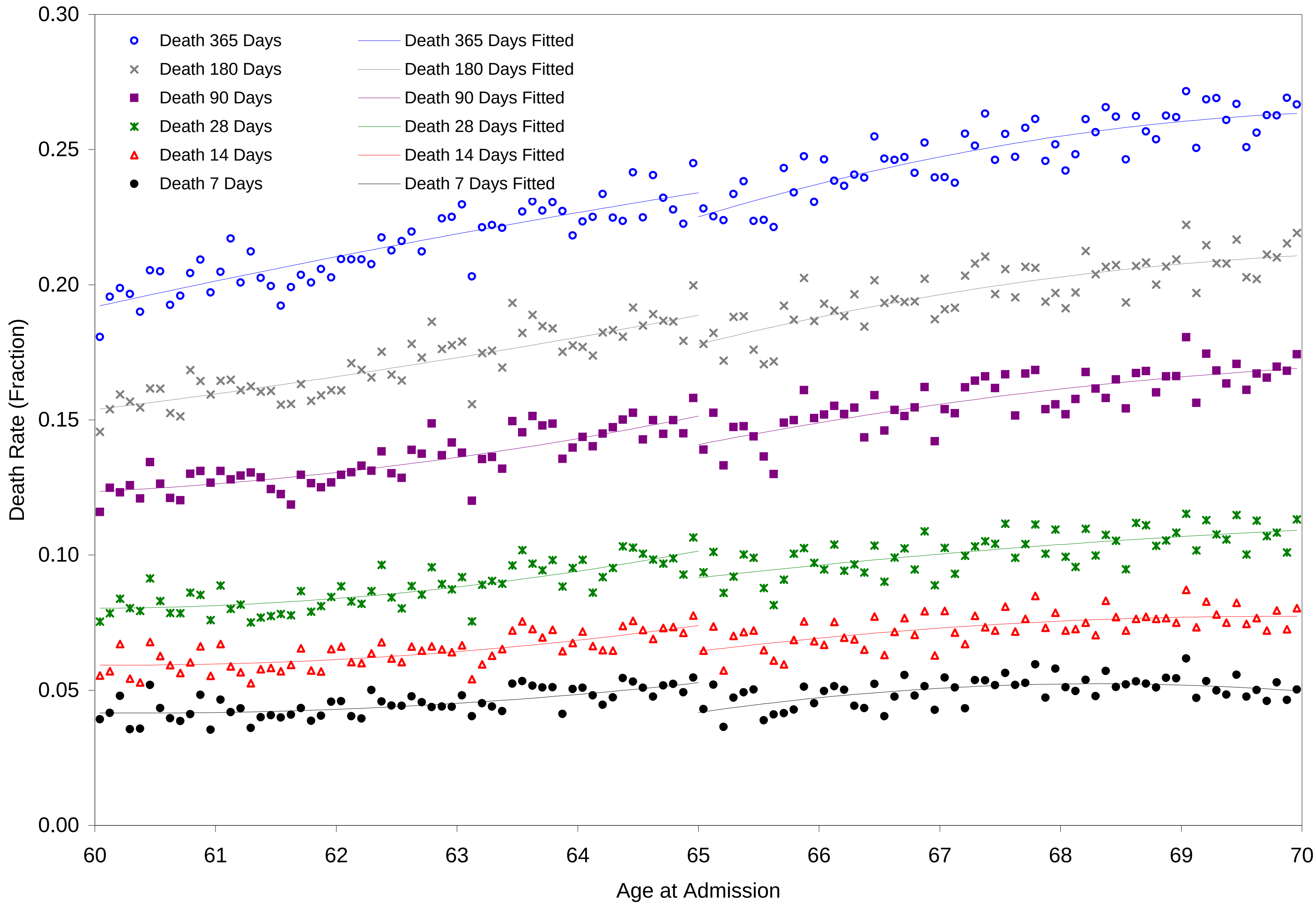
Notes: See notes for Figure 2. In this figure the y-axis represents the fraction of patients with different classes of primary insurance coverage. Sample includes 425,315 patients with non-deferrable primary diagnoses, defined as unplanned admissions through the emergency department for diagnoses with a t-statistic for the test of equal weekday and weekend admission rates of 0.965 or less. Medicare eligibility status of patients within one month of their 65th birthday is uncertain and we have excluded these observations.

Figure 5: Three Measures of Inpatient Treatment Intensity



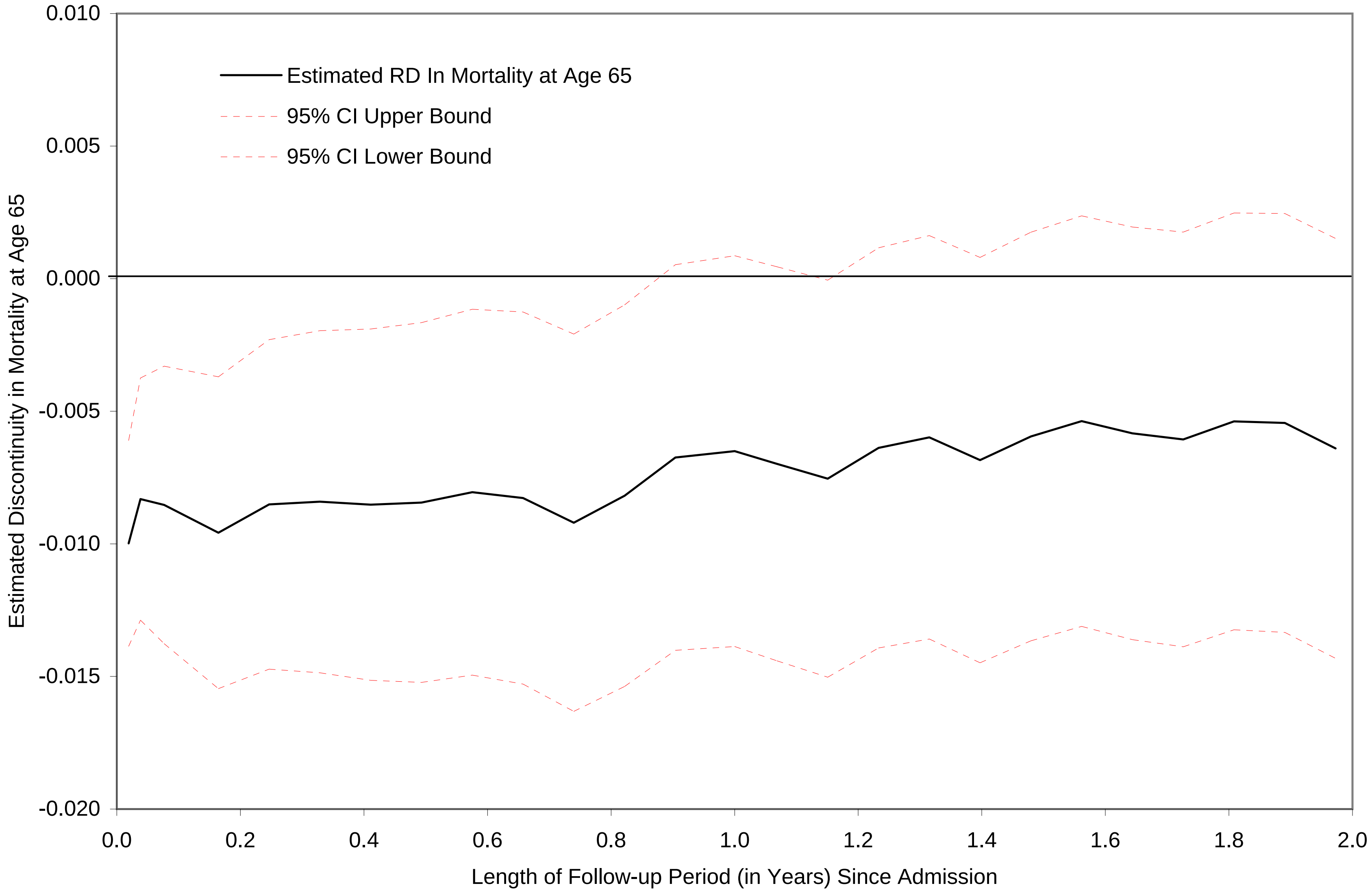
Notes: See notes to Figure 4. Sample includes unplanned admissions through the emergency department for diagnoses with a t-statistic for the test of equal weekday and weekend admission rates of 0.965 or less. In this figure the sample is further restricted to patients with a valid SSN (407,386 observations). Sample for log list charges excludes patients admitted to Kaiser hospitals. Length of stay, number of procedures, and list charges are cumulated over all consecutive hospitalizations. List charges are measured in 2002 dollars.

Figure 6: Patient Mortality Rates over Different Follow-up Intervals



Notes: See notes to Figure 4. Sample includes unplanned admissions through the emergency department for diagnoses with a t-statistic for the test of equal weekday and weekend admission rates of 0.965 or less. In this figure the sample is further restricted to patients with a valid SSN (407,386 observations). Deaths include include in-hospital and out-of-hospital deaths.

Figure 7: Estimates of the Discontinuity in Mortality Rates at Age 65 Over Various Follow-up Periods



Notes: See notes to Figure 6. The estimates in this figure are from a regression with a quadratic polynomial in age fully interacted with a dummy for age over 65. The regressions also include a dummy for patients within one month of their 65th birthday, month and year dummies, fixed effects for the primary diagnosis, and dummies for race, gender, and admissions on Saturday or Sunday. Regression discontinuities are estimated for probability of death within 7, 14, 28 days, and then at 30 day intervals. The estimates and associated 95 percent confidence intervals from each regression are then linearly interpolated in the figure.

Table 1: Ten Most Common Diagnoses (ICD-9) in Non-Deferrable Admissions Sample

	Number of Admissions	Mean Length of Stay	Mean Number of Procedures	Mean Total List Charges	28-Day Death Rate
Obstructive chronic bronchitis w/ acute exacerbation	61,558	6.2	1.2	26,000	4.7
Respiratory failure	24,328	13.7	3.7	72,400	22.5
AMI of other inferior wall (1st episode)	21,192	7.2	5.1	59,000	6.9
AMI of other anterior wall (1st episode)	15,727	7.8	5.3	63,400	10.6
Intracerebral hemorrhage	10,755	17.8	3.6	68,700	29.6
Chronic airway obstruction, n.e.c.	9,102	6.5	1.5	22,100	7.7
Fracture of neck of femur intertrochanteric section	6,868	14.2	2.7	44,100	2.9
Cerebral artery occlusion, unspecified	5,782	15.2	3.7	33,900	8.1
Convulsions unknown cause	5,338	5.1	1.2	22,800	3.1
Asthma, unspecified with status asthmaticus	5,095	4.6	1.1	17,800	0.9

Note: Length of stay, procedure count and hospital list charges are totals for all sequential hospital stays. Sample is drawn from California Hospital Discharge records for 1992-2002 for patients between the ages of 60 and 70 who were admitted to the hospital through the Emergency Department for an unplanned cause. Diagnoses are only included if a t-test for the equality of admission rates on weekends and weekdays has a t-statistic less than 0.965. List charges are in 2002 dollars.

Table 2: Regression Discontinuity Models for Log (Number of Admissions) to California Hospitals by Age of Patient at Admission

	Non-ED or Planned		ED and Unplanned		Weekend t-stat > 6.62	
	(1)	(2)	(3)	(4)	(5)	(6)
Age Over 65 (×100)	11.9	12.0	2.4	2.6	3.2	3.3
	(0.5)	(0.5)	(0.5)	(0.5)	(1.0)	(1.1)
Dummy for Just Under 65	No	Yes	No	Yes	No	Yes
	Weekend t-stat 2.54-6.62		Weekend t-stat 0.96-2.54		Weekend t-stat < 0.96	
	(7)	(8)	(9)	(10)	(11)	(12)
Age Over 65 (×100)	3.6	3.7	2.7	3.0	0.6	0.6
	(0.9)	(1.0)	(0.9)	(1.0)	(0.9)	(0.9)
Dummy for Just Under 65	No	Yes	No	Yes	No	Yes

Note: Standard errors in parentheses. Dependent variable in all models is the log of the number of admissions by patient's age (in days) at admission, for patients between 60 and 70 years of age (3,652 observations). Count of admissions is based on Hospital Discharge Records for California, and includes admissions from January 1, 1992 to November 30, 2002. All models include a second order polynomial in age (in days) fully interacted with a dummy for age over 65. Models in even numbered columns include a dummy for people who are within 1 month of their 65th birthday, whose Medicare eligibility status at the time of admission is indeterminant. Sample in columns 1-2 includes admissions that were either planned or did not occur through the Emergency Department (ED). Samples in all other columns include admissions that were unplanned and occurred through the ED. Samples in columns 5-12 are further restricted by including only admissions for diagnoses (ICD-9 classifications) for which the t-test for equality of weekend and weekday admission rates is in the range indicated.

Table 3: Regression Discontinuity Models for Probability of Different Forms of Primary Insurance Coverage

	Medicare		Private		Medicaid		Uninsured	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age Over 65 (×100)	43.9	47.5	-24.8	-26.8	-10.1	-10.8	-7.4	-8.0
	(0.4)	(0.4)	(0.4)	(0.4)	(0.3)	(0.3)	(0.2)	(0.2)
Additional Controls	No	Yes	No	Yes	No	Yes	No	Yes
Mean of Dependent Variable for Patients Age 64-65 (×100)	24.0		43.3		43.3		9.7	

Notes: standard errors in parentheses. Dependent variable is indicator for type of insurance listed as "primary insurer" on discharge record. Sample includes 425,315 observations on patients between the ages of 60 and 70 admitted to California hospitals between January 1 1992 and November 30, 2002 for an unplanned admission through the Emergency Department, with diagnosis (ICD-9) included in the group for which the t-test for equality of weekend and weekday admission rates is less than 0.96 in absolute value. All models include second order polynomial in age (in days) fully interacted with dummy for age over 65 and are fit by OLS. Models in even-numbered columns include the following additional controls: a dummy for people who are within 1 month of their 65th birthday; dummies for month, year, gender, race/ethnicity, and admission on Saturday or Sunday; and a complete set of unrestricted fixed effects for each ICD-9 admission diagnosis.

Table 4: Regression Discontinuity Models for Changes in Treatment Intensity

	Length of Stay (Days)		Number of Procedures		Log List Charges (x100)	
	(1)	(2)	(3)	(4)	(5)	(6)
Age Over 65 (×100)	0.37	0.35	0.09	0.11	2.5	2.6
	(0.24)	(0.26)	(0.03)	(0.03)	(1.1)	(1.0)
Additional Controls	No	Yes	No	Yes	No	Yes
Mean of Dependent Variable for Patients Age 65-65	8.12		2.50		9.87	

Notes: standard errors in parentheses. Dependent variable is length of stay in days (columns 1-2), number of procedures peformed (columns 3-4) and log of total list charges (columns 5-6). Sample includes 407,386 (352,652 in columns 5-6) observations on patients with a valid SSN between the ages of 60 and 70 admitted to California hospitals between January 1, 1992 and November 30, 2002 for an unplanned admission through the Emergency Department. Data on list charges is missing for Kaiser hospitals. See note to Table 3 for additional details on sample, and list of additional covariates included in even-numbered columns.

Table 5: Regression Discontinuity Estimates of Changes in Mortality Rates

	Death Rate in:					
	7 Days	14 Days	28 Days	90 Days	180 Days	365 Days
Estimated Discontinuity at Age 65 (×100)						
1. Fully Interacted Quadratic	-1.1	-1.0	-1.1	-1.1	-1.2	-1.0
With no Additional Controls	(0.2)	(0.2)	(0.3)	(0.3)	(0.4)	(0.4)
2. Fully Interacted Quadratic Plus	-1.0	-0.8	-0.9	-0.9	-0.8	-0.7
Additional Controls	(0.2)	(0.2)	(0.3)	(0.3)	(0.3)	(0.4)
3. Fully Interacted Cubic Plus	-0.7	-0.7	-0.6	-0.9	-0.9	-0.4
Additional Controls	(0.3)	(0.2)	(0.4)	(0.4)	(0.5)	(0.5)
4. Local Linear Regression	-0.8	-0.8	-0.8	-0.9	-1.1	-0.8
Procedure Fit Separately to Left and Right with Rule-of-thumb Bandwidths	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)	(0.3)
Mean of Dependent Variable (%)	5.1	7.1	9.8	14.7	18.4	23.0

Notes: standard errors in parentheses. Dependent variable is indicator for death within interval indicated by column heading. Entries in rows 1-3 are estimated coefficients of dummy for age over 65 from models that include a quadratic polynomial in age (rows 1-2) or a cubic polynomial in age (row 3) fully interacted with a dummy for age over 65. Models in rows 2-3 include the following additional controls: a dummy for people who are within 1 month of their 65 birthday, dummies for year, month, gender, race/ethnicity, and Saturday or Sunday admissions, and unrestricted fixed effects for each ICD-9 admission diagnosis. Entries in row 4 are estimated discontinuities from a local linear regression procedure, fit separately to the left and right, with independently selected bandwidths from a rule-of-thumb procedure suggested by Fan and Gijbels (1996). Sample includes 407,386 observations on patients between the ages of 60 and 70 admitted to California hospitals between January 1 1992 and November 30, 2002 for an unplanned admission through the Emergency Department, who have non-missing Social Security numbers.

Table 6: Estimated Lower Bounds for Change in 28-Day Mortality at Age 65

	All Admissions (1)	Planned or Non-ED Admission (2)	Unplanned ED Admission (3)	Unplanned ED Admissions (by Range of t-test for Weekend Admission Rate) t>6.62 (4)	2.54<t<6.51 (5)	0.96<t<2.54 (6)	t<0.96 (7)
1. Estimated Discontinuity in Log of Number of Admissions at Age 65 (×100)	7.12	11.85	2.43	3.23	3.57	2.70	0.56
2. Estimated Discontinuity in Probability of Death at Age 65 (×100)	-0.46	-0.29	-0.49	0.27	-0.63	-0.45	-1.09
3. Mean Probability of Death for People Age 64 (×100)	5.10	3.29	6.86	2.68	7.41	6.87	10.25
4. Estimated "Worst Case" Bound on Selection Bias Component of Change in Death Rate at Age 65	-0.33	-0.36	-0.15	-0.10	-0.24	-0.17	-0.05
5. Estimated Lower Bound for Causal Effect of Reaching Age 65 on Death Rate (standard error)	-0.13 (0.07)	0.06 (0.09)	-0.33 (0.12)	0.37 (0.16)	-0.39 (0.25)	-0.27 (0.24)	-1.04 (0.29)
6. Share of Admissions in Column Sample	1.00	0.50	0.50	0.11	0.13	0.12	0.12

Notes: Row 1 presents estimated regression discontinuities in the log of the number of hospital admissions at age 65, from a specification fit to admission counts by age for patients age 60 to 70 (3,652 observations) that includes a quadratic polynomial in age, fully interacted with a dummy for age over 65. Row 2 presents estimated regression discontinuities in the probability of death at age 65 from a specification fit to mean death rates by age at admission data for patients age 60 to 70 (3,652 observations) that includes a quadratic polynomial in age, fully interacted with a dummy for age over 65. Row 3 presents estimated mean probabilities of death within 28 days of admission for patients who are 64 years old. Row 4 presents the estimated worst case bound on the selectivity component of the change in death rates at age 65, computed as −row 1 × (row 2 + row 3)/100. Row 5 is the estimated lower bound on the causal effect of reaching age 65 on the 28-day death rate, computed as row 8−row 4. The standard error is computed by the delta method, using the sampling errors of the estimates of the entries in rows 1, 2, and 3, and their sampling covariances.

Online Appendix for Card, Dobkin and Maestas, “Does Medicare Save Lives?”

I. Data Appendix

We use annual hospital discharge files from the state of California for the period 1992-2002. These files represent a census of discharges from state-regulated acute care hospitals, collected by OSHPD, the Office of Statewide Health Planning and Development, under California Code of Regulations, Title 22. The data set excludes people admitted to federally regulated hospitals such as VA hospitals. Our working sample includes people admitted to the hospital between January 1, 1992 and November 30, 2002, whose age at admission is between 60 and 70. The discharge files include the patient’s sex, race/ethnicity, zip code of residence, date of admission, source of admission, route of admission (ED or not), type of admission (scheduled, unscheduled, new birth), principal diagnosis, other diagnoses present at admission, a list of procedures performed, total list charges, expected payer code, disposition of patient (routine discharge, transfer to another hospital, etc.) and date of discharge. We obtained a restricted use version of the file which also includes the patient’s age in days at admission (calculated from the exact date of admission and exact date of birth). The file also includes a unique patient identifier and an indicator for whether the patient provided a valid SSN.

We also obtained from OSHPD a separate file constructed by OSHPD by matching individuals in the discharge data base to state records of death, by name/SSN/date of birth. We merged this file to the discharge record file by patient identifier.

In our analysis we combine all consecutive hospital admissions into a single record defined by the first date of admission (and by the descriptors associated with this first admission). We cumulate the length of stay, the number of procedures, and list charges across all stays.

II. Description of Figures and Tables

IIa. Figures

Figure A: Employment Rates by Age

This figure shows employment rates by quarter of age, using data from the 1992-2003 NHIS. There is no discontinuity in the likelihood of working at exactly age 65.

Figure B: Proportion of Admissions that Occur on the Weekend by ICD-9

This figure shows how the distribution of the fraction of weekend admits over the diagnosis codes in our sample of non-deferrable admissions centers tightly around 2/7 in contrast to the distributions over all diagnosis codes and those associated with ED admissions.

Figure C: Proportion on Medicare by Age in Days

This figure shows the fraction of admitted patients in our non-deferrable admission sample who are recorded as having Medicare as their primary insurance provider by age in days for a narrow window around age 65. This fraction is relatively flat for people up to a month before their 65th birthday, then rises linearly in the 31 days before reaching age 65, as would be expected given Medicare eligibility rules and a uniform distribution of birthdates.

Figure D: Age Profile of Charlson Comorbidity Scores

This figure shows the age profile in the Charlson comorbidity scores for the non-deferrable sample. The Charlson co-morbidity index is a weighted count of the presence of 19 diseases. There is no discernable evidence of a drop in severity at age 65; in fact, formal RD analysis (presented in Table B) on the age profile indicates a small but statistically insignificant *increase* in severity.

Figure E: Predicted Mortality Probabilities

This figure shows predicted 7-day and 28-day mortality rates based on linear probability models including all available covariates for an admission (age, race/ethnicity, gender, year, month, and day of admission, and principal diagnosis fixed effects). The age profiles of predicted mortality are extremely smooth, and show no jump at age 65. In an RD specification with a quadratic in age and a dummy for over 65, interacted with the linear and quadratic terms, the t-statistics for the post-65 coefficient are 0.4 (7 day mortality) and 0.25 (28 day mortality), providing no evidence that the observable health of the sample changes at age 65. The results are similar for 14-day, 90-day, and 365-day mortality.

Figure F: Age Profile of Standard Deviation of List Charges

In this figure, we evaluate the effect of Medicare eligibility on the *distribution* of list charges. There is no visual evidence of a large or statistically significant effect on the dispersion in charges at age 65. This is confirmed by formal RD estimates presented in Table C, which also presents estimates for total number of procedures and length of stay.

Figure G: Age Profiles of 75th and 90th Percentiles of List Charges

In this figure, we evaluate the effect of Medicare eligibility on the *distribution* of list charges. There is no visual evidence of a large or statistically significant effect on the dispersion in charges at age 65. This is confirmed by formal RD estimates presented in Table C, which also presents estimates for total number of procedures and length of stay.

Figure H: Transfer after Admission to the Hospital

This figure shows the age profiles in transfers within the same hospital and to other hospitals.

Figure I: Readmitted to Hospital

This figure shows the age profiles in readmissions to the hospital within 7 and 28 days of the initial hospital stay.

Figure J: Comparison of Alternative Parametric Fits for RD Model of Death within 28 days

This figure presents a comparison of fits from linear, quadratic, and cubic models for 28-day mortality.

Figure K: Local Linear Regression Estimates of 28-day Mortality Rates from Left and Right of Age 65 Threshold -- Varying Bandwidths, Rectangular Kernel

This figure presents LLR-based estimates of the 28-day mortality rate for patients on each side of the age 65 boundary, using all possible bandwidths between 1 month and 5 years and a rectangular kernel.

IIb. Tables

Table A: Comparison of RD Models for the Log (number of admissions) with Quadratic and Cubic Polynomials

In Table 2, we showed that there is no RD in admissions for the non-deferrable subsample (Weekend t-stat<0.96) using a specification that contained a quadratic polynomial in age. In Table A, we present two models for each patient group: one that uses a quadratic polynomial (reproduced from the specifications in the even-numbered columns of Table 2) and a second that uses a cubic polynomial in age. The cubic models give very similar estimated discontinuities at age 65.

Table B: Regression Discontinuity Models for Charlson Comorbidity Score

This table presents the formal RD estimates that accompany Figure D. Across three different specifications there is no statistically significant change in the average severity of admissions at age 65. Although insignificant, the point estimate itself is slightly positive, suggesting that if anything, our sample may become slightly *less* healthy after age 65.

Table C: Regression Discontinuity Models for Upper Quantiles and Standard Deviation of Treatment Intensity Measures

This table accompanies Figures F and G, showing formal RD estimates for the standard deviation, 75th, and 90th percentiles of the distribution of length of stay, list charges, and total number of procedures.

Table D: Regression Discontinuity Models for Specific Procedures for Patients Admitted with Two Leading Conditions

This table shows RD estimates for two major conditions in our sample, AMI and obstructive chronic bronchitis. We find a relatively large increase in procedures for AMI (a procedure-intensive diagnosis) and little change for obstructive chronic bronchitis (a non-procedure-intensive diagnosis).

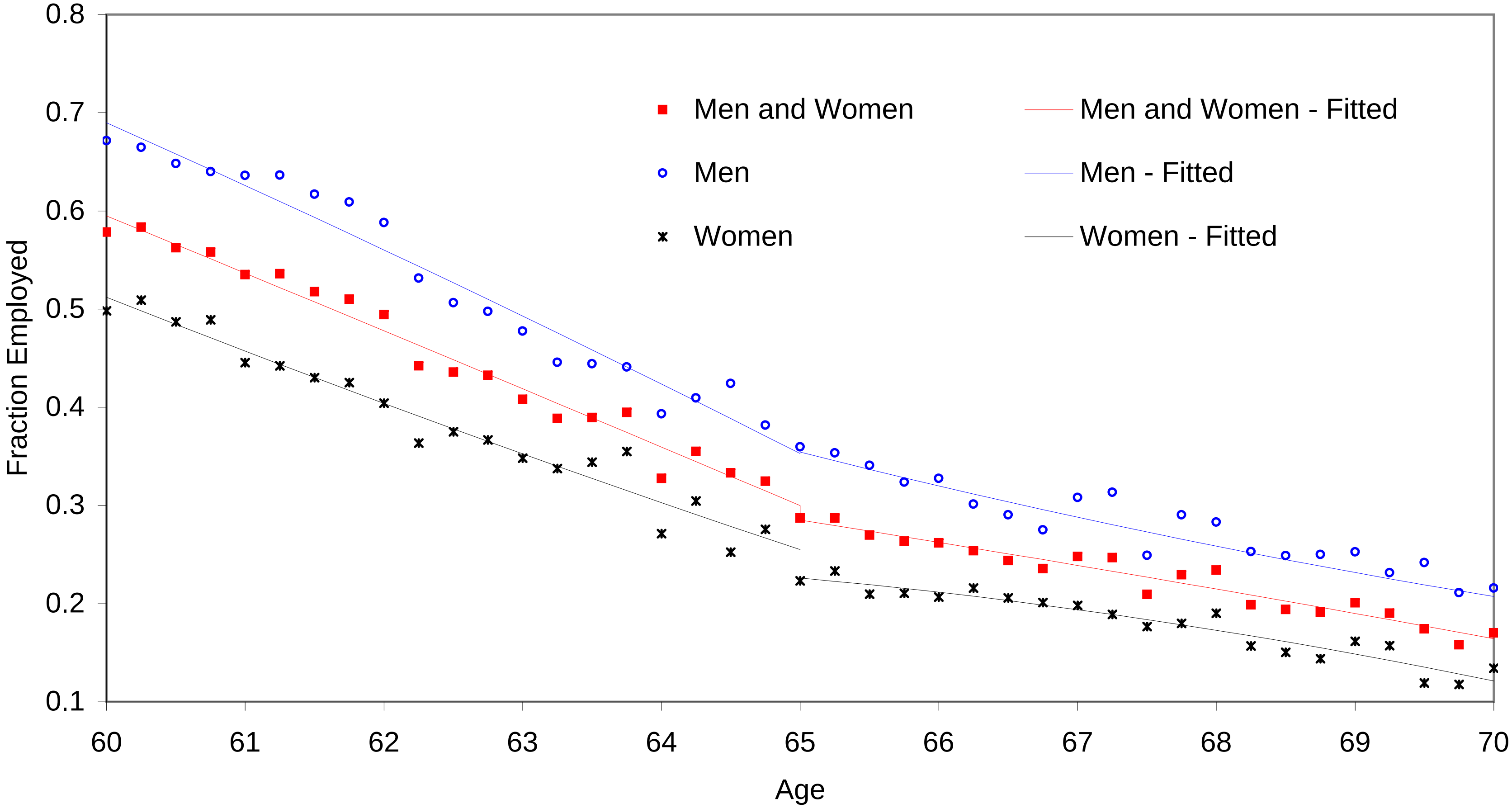
Table E: Regression Discontinuity Estimates of Changes in Transfer and Readmission Probabilities

This table accompanies Figures H and I, showing formal RD estimates of transfers across hospitals, within hospitals, and readmissions within 7 and 28 days of discharge. Four specifications are presented for each outcome.

Table F: Comparison of Linear Probability and Logit Specifications of Regression Discontinuity Model for Probability of Death

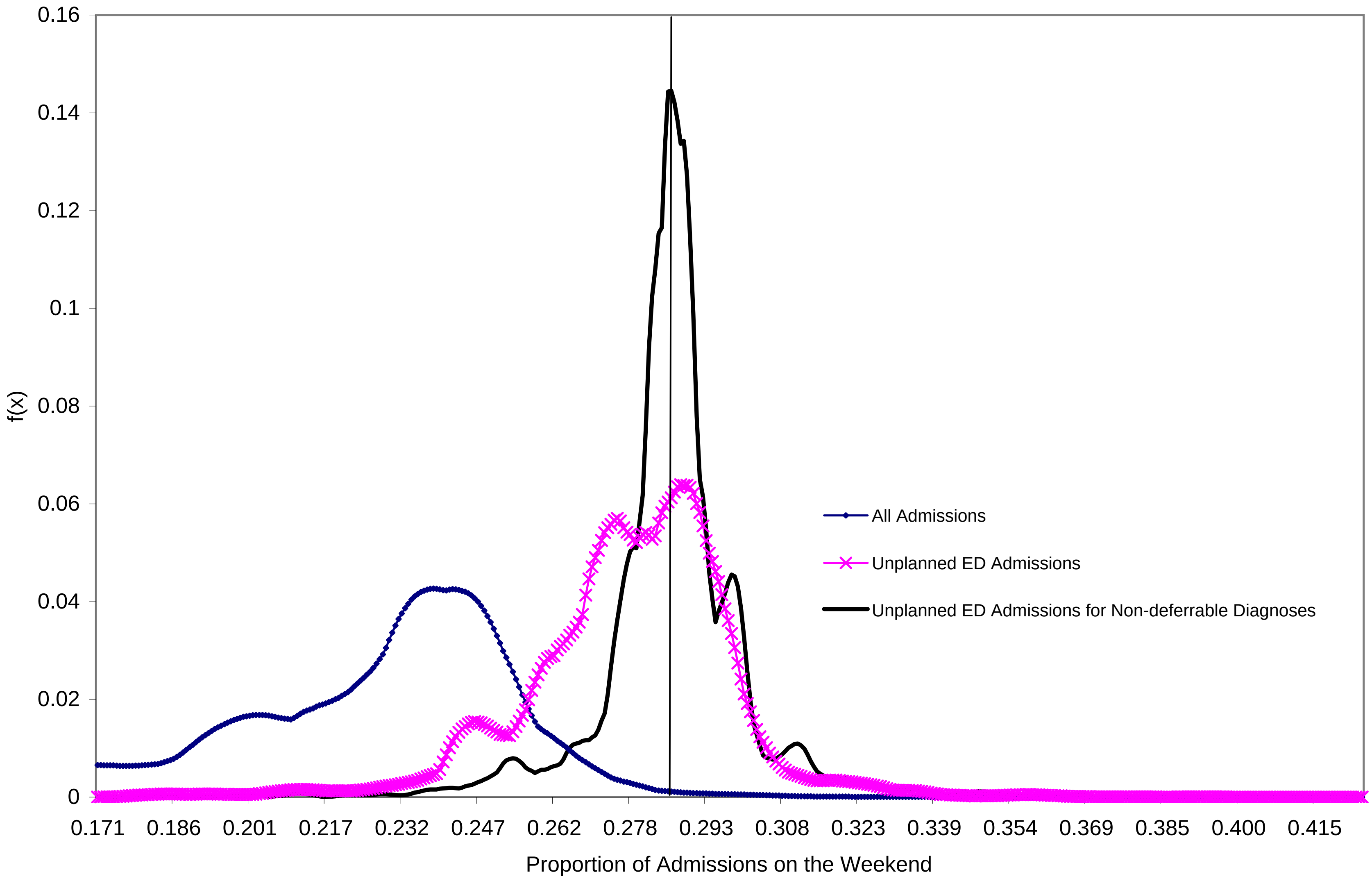
This table presents a comparison between coefficient estimates from our linear probability models for mortality and marginal effects from alternative logit specifications. The effects are nearly identical across the specifications.

Appendix Figure A: Employment Rates by Age from 1992-2003 NHIS



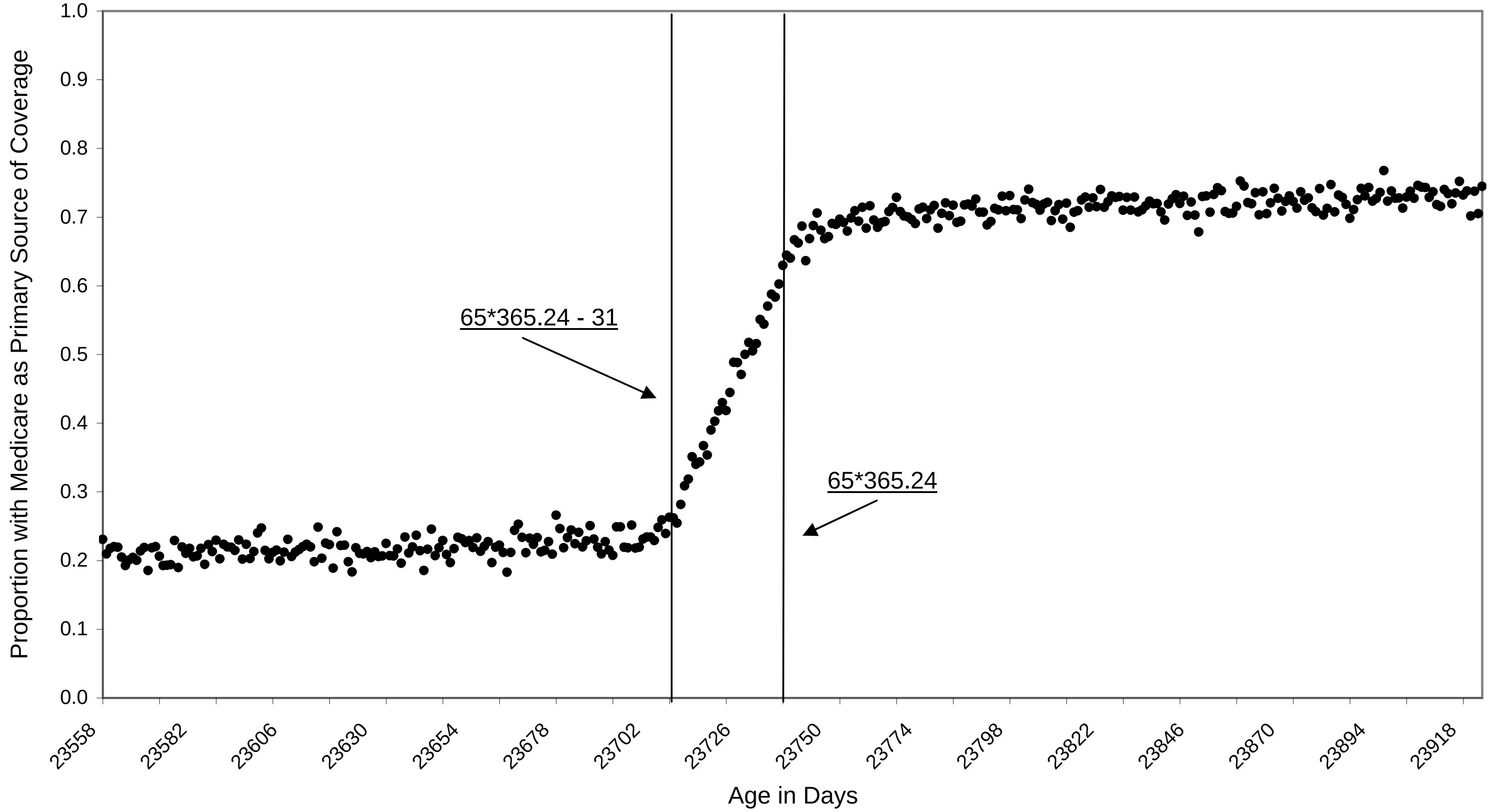
Note: samples are derived from 1992-2003 National Health Interview Surveys, and include people whose age at the interview is between 60 and 70. Sample sizes are 37,820 men, 44,285 women, and 82,105 combined. Fitted models include dummy for age over 65, and quadratic in age, fully interacted with age over 65 dummy. Estimated discontinuities (clustered standard errors) are: for combined sample -0.015 (0.010); for men 0.002 (0.017); for women -0.029 (0.015).

Appendix Figure B: Proportion of Admissions that Occur on the Weekend by ICD-9



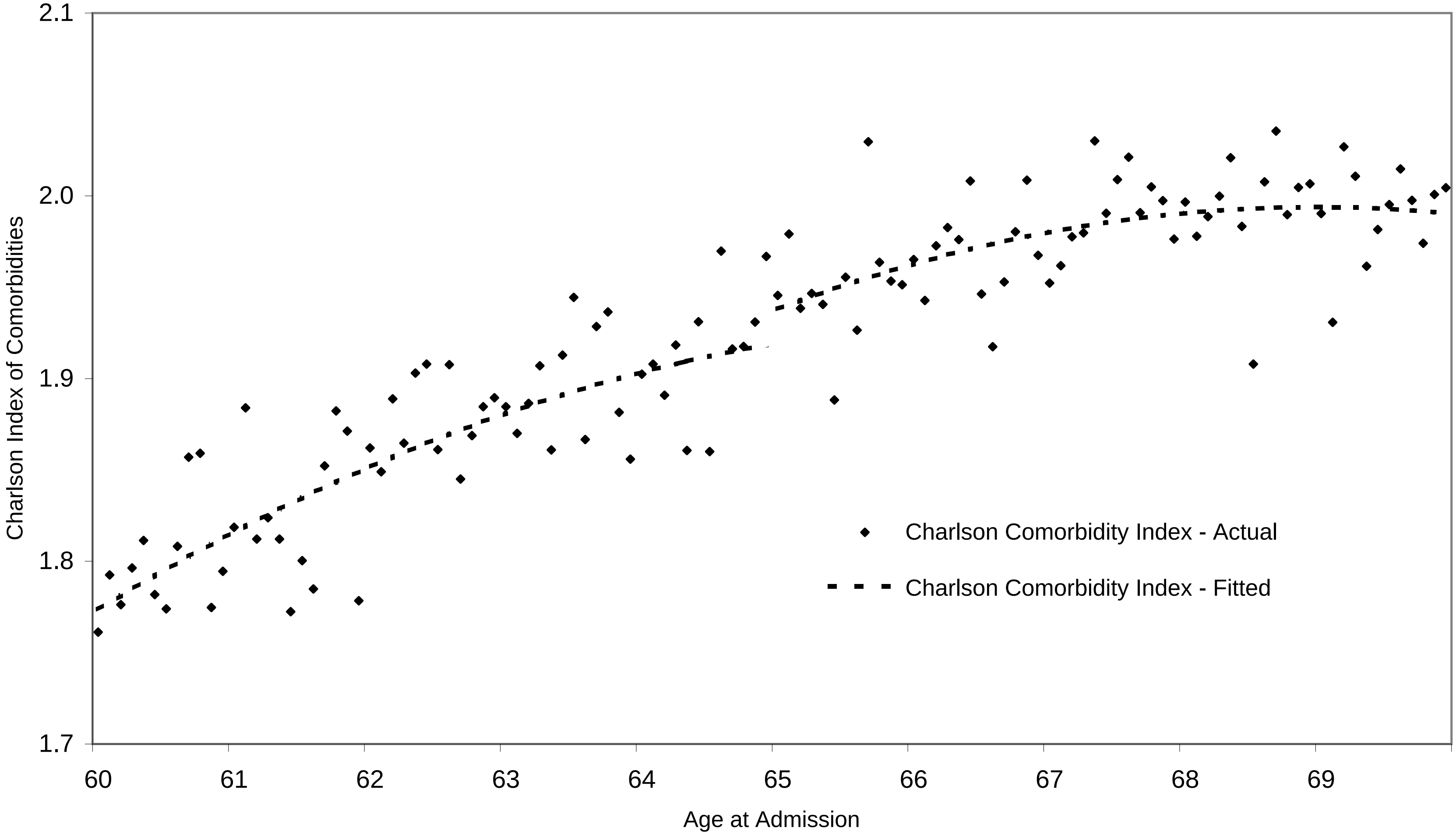
Notes: Figure shows smoothed densities of the fraction of patients with a given admission diagnosis (ICD-9) admitted on weekend. Density for "All Admissions" includes all admission diagnoses for all patients in Hospital Discharge Records for California for January 1, 1992 to November 30, 2002. Density for "Unplanned ED Admissions" includes weekend fractions among unplanned admissions through the emergency department. Density for "Unplanned ED Admissions for Non-deferrable Diagnoses" includes weekend fractions among unplanned admissions through the emergency department for subset of diagnoses with t-test for fraction of weekend admissions = 2/7 having absolute value less than 0.965.

Appendix Figure C: Proportion of Patients with Medicare as Primary Insurer by Age in Days



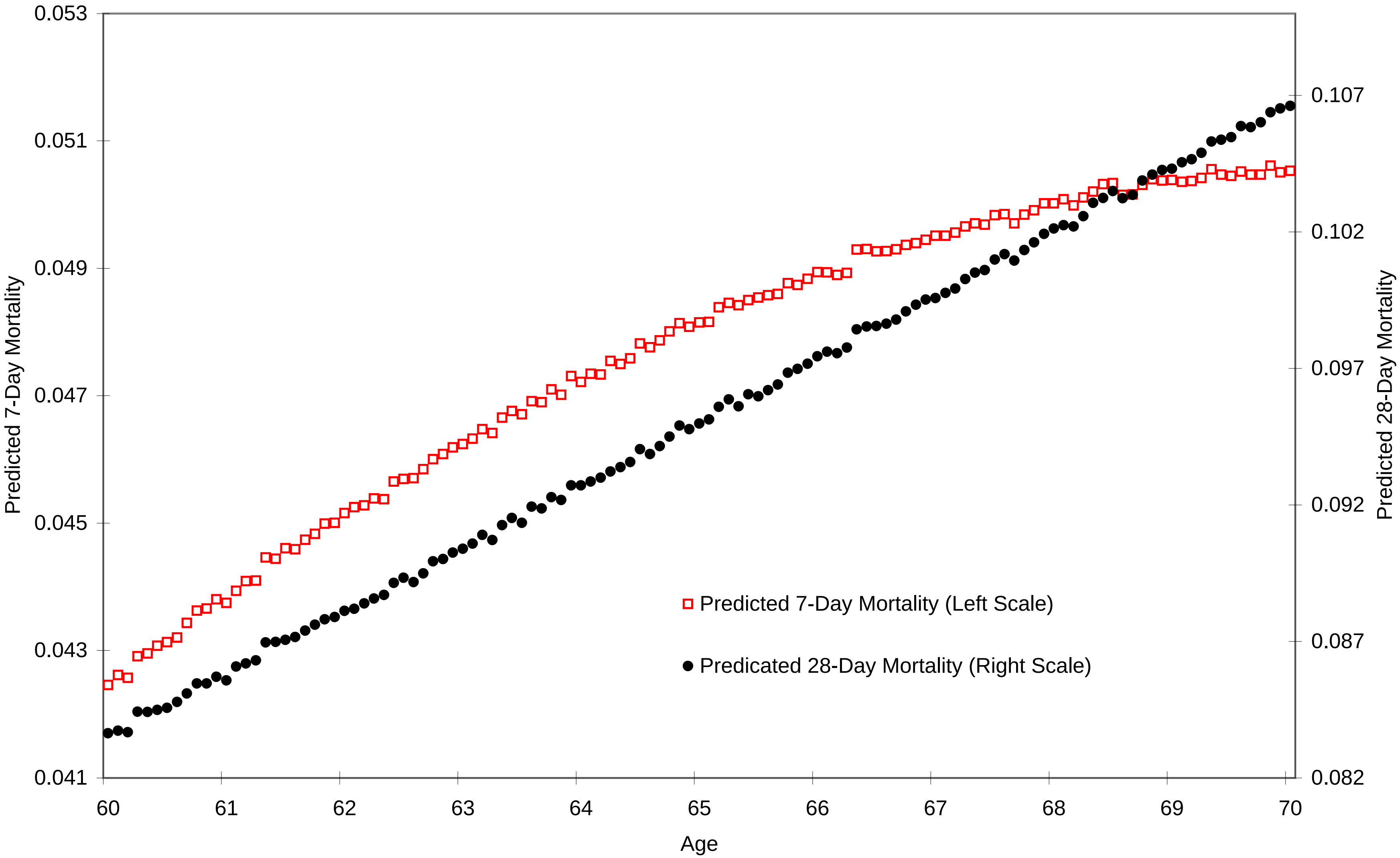
Note: Data are drawn from California Hospital Discharge Records from January 1, 1992 to November 30, 2002. Each point is the fraction of patients admitted at a particular age in days that has Medicare as their primary source of insurance coverage. Patients are potentially eligible for Medicare on 1st of month in which they reach age 65. Thus, the youngest age at which a patient is potentially eligible based on age (rather than disability) is 65*365.24- 31 days, and the oldest is 65*365.24.

Appendix Figure D: Age Profile of Charlson Comorbidity Scores



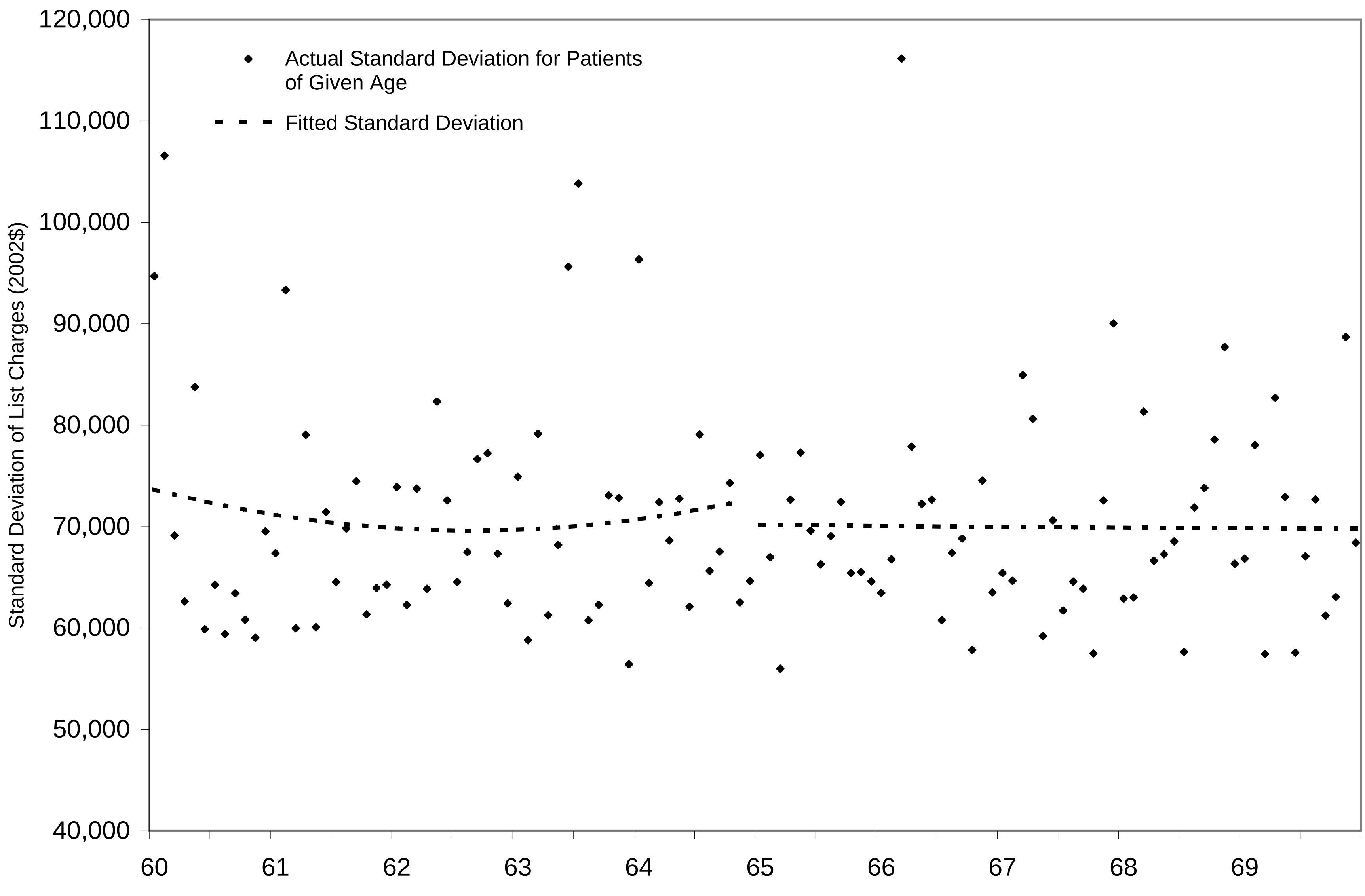
Notes: Age profiles of treatment intensity are estimated from Hospital Discharge Records for California, and include unplanned admissions through the ED occurring between January 1, 1992 and November 30, 2002 for diagnoses with a t-statistic for the test of equal weekday and the weekend admission rates of 0.965 or less. The Charlson Comorbidity Score is a weighted sum of the number of comorbities present at admission.

Appendix Figure E: Predicted Mortality Rates Based on Patient Characteristics at Admission



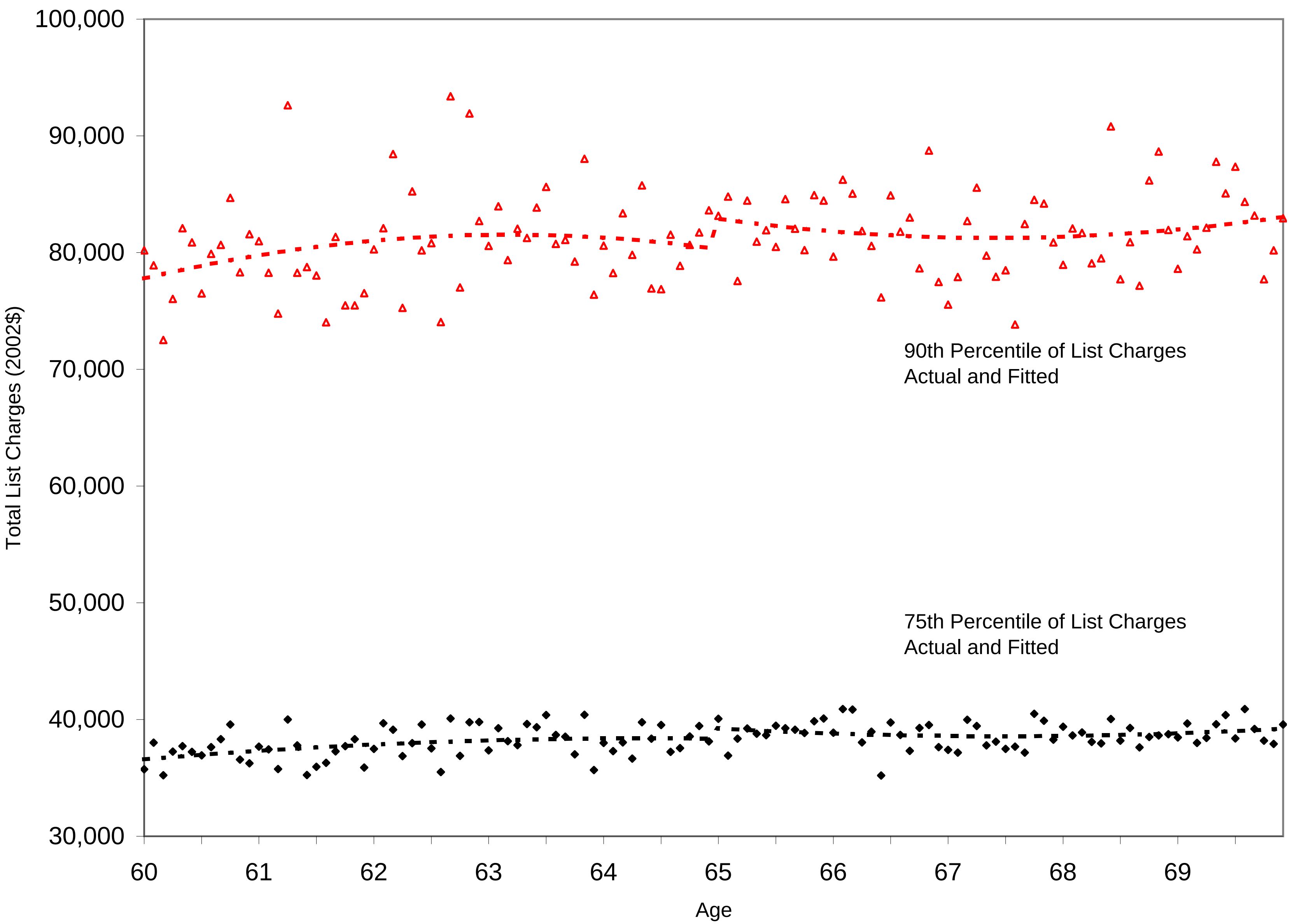
Notes: Points represent average values of predicted mortality at 7 or 28 days for patients with a given age in months at admission. Sample includes unplanned admissions through the emergency department for diagnoses with a t-statistic for the test of equal weekday and weekend admission rates of 0.965 or less. Predicted mortality is based on a linear probability model that includes a quadratic in age (in days), fixed effects for each admission diagnosis, dummies for gender, race, ethnicity, year, month and day of the week of admission to the hospital.

Appendix Figure F: Age Profile of Standard Deviation of List Charges



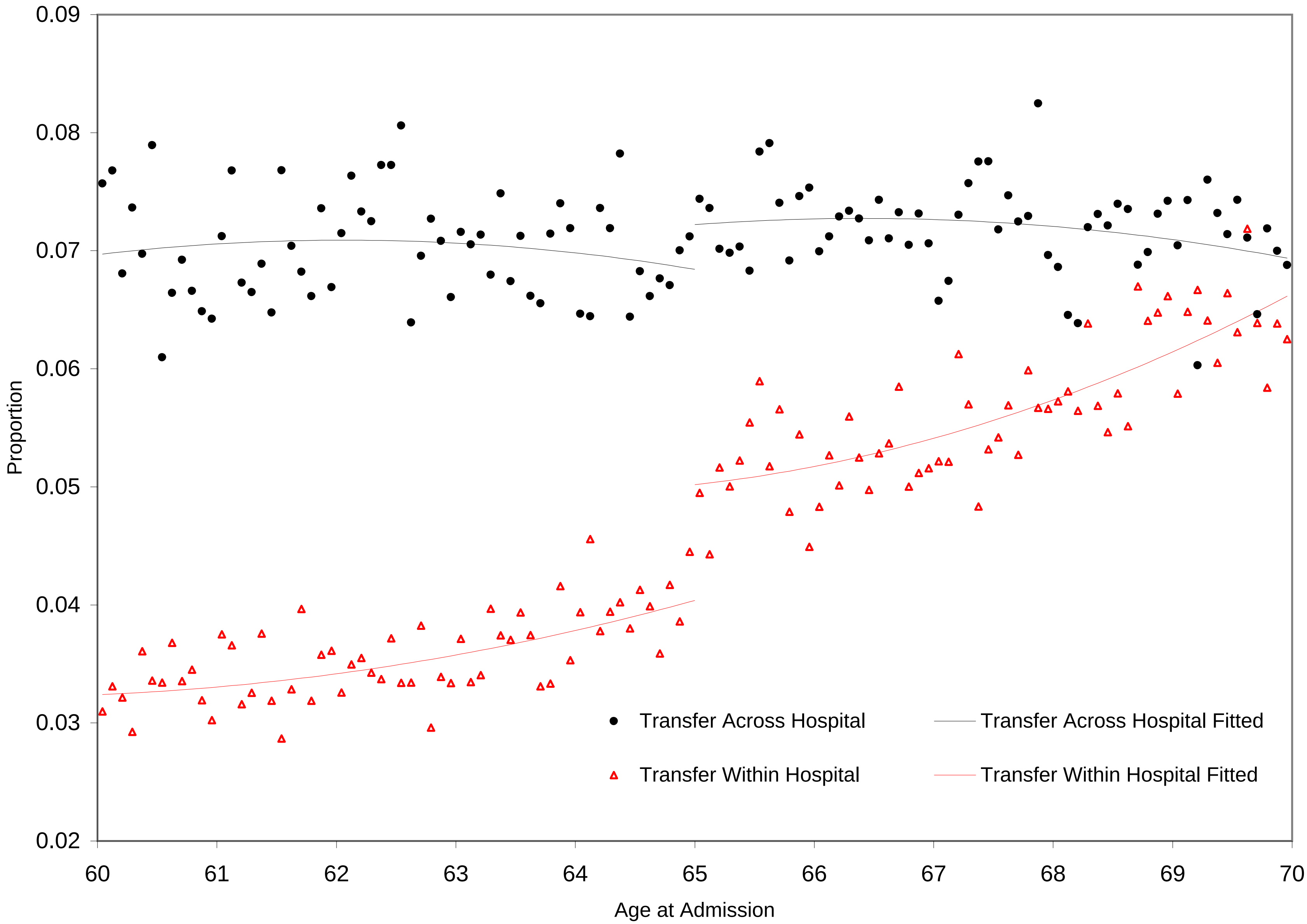
Notes: The standard deviation of list charges is computed for all patients admitted to the hospital at a particular age in days. See Table 4 for sample description. List charges (measured in $2002) from all transfers are added to the charges from the first unit the patient was admitted to. List charges are not available for Kaiser hospitals.

Appendix Figure G: Age Profiles of 75th and 90th Percentiles of List Charges



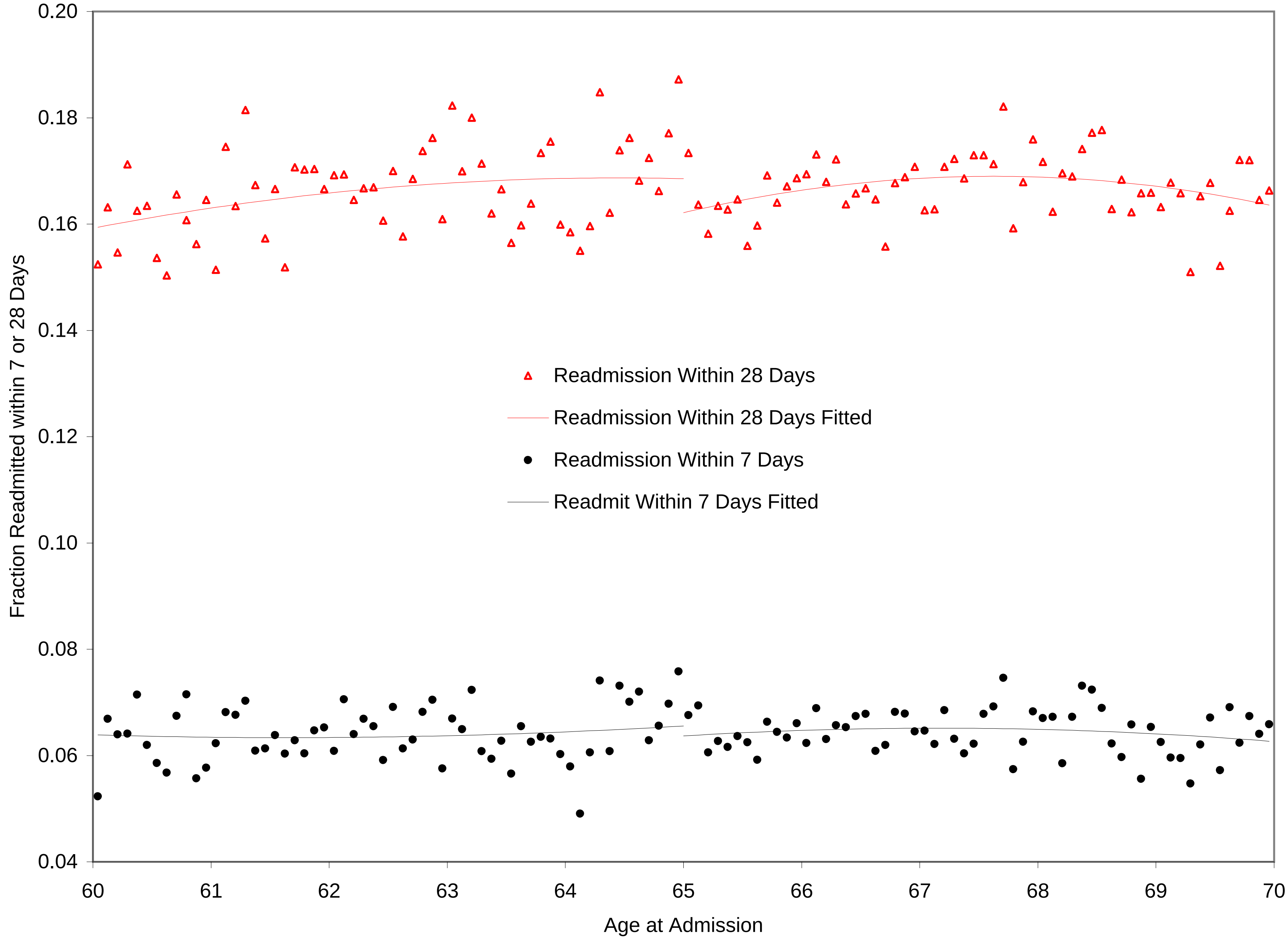
Notes: See notes from Appendix Figure F.

Appendix Figure H: Probabilities of Transfer after First Admission to the Hospital



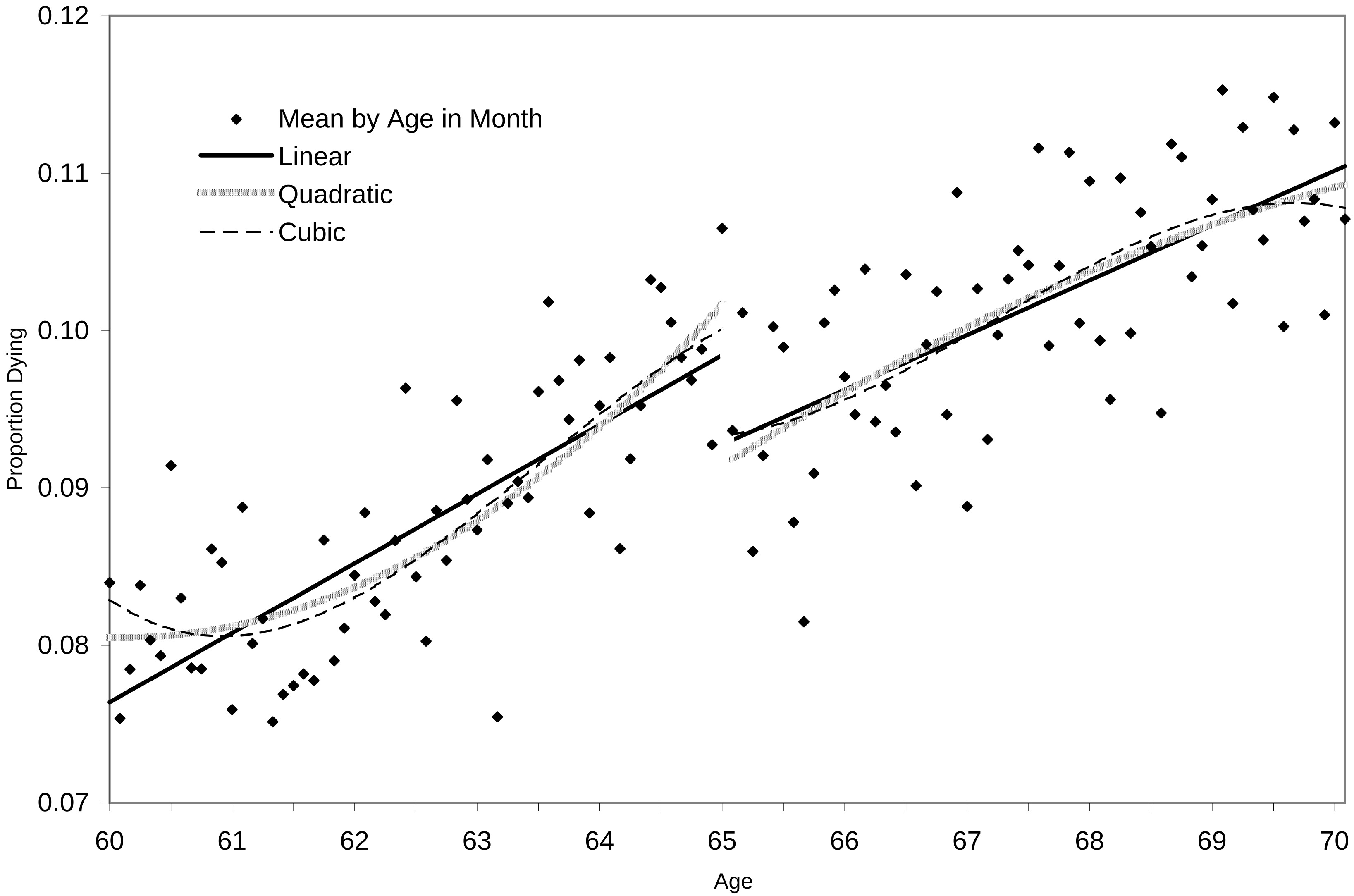
Notes: See notes to Figure 5. Sample excludes patients with invalid SSN's.

Appendix Figure I: Probabilities of Readmission to the Hospital



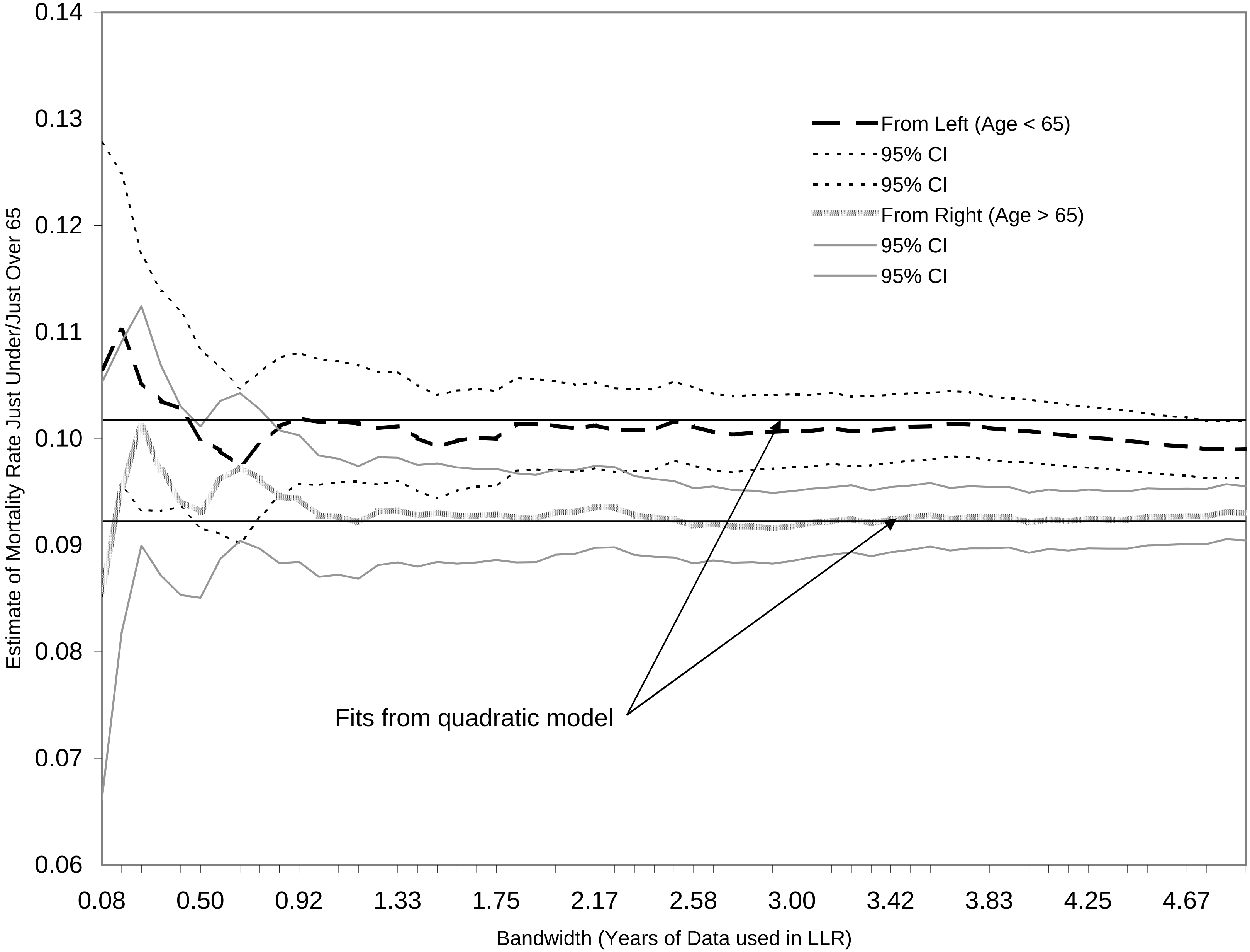
Notes: See notes to Figure 5. Sample excludes patients with invalid SSN's. Days to readmission are computed from date of discharge.

Appendix Figure J: Comparison of Alternative Parametric Fits for RD Model of Death within 28 days



Notes: Figure shows predicted age profile for the probability of death within 28 days from models with linear, quadratic and cubic functions of age (in days), fully interacted with dummy for age over 65.

Appendix Figure K: Local Linear Regression Estimates of 28-day Mortality Rates From Left and Right of Age 65 Threshold -- Varying Bandwidths, Rectangular Kernel



Appendix Table A: Estimated Discontinuities in Log (Number of Admissions) - Quadratic vs. Cubic Polynomials

	Non ER or Planned		ER and Unplanned		Weekend t-stat > 6.62	
	(1)	(2)	(3)	(4)	(5)	(6)
Age Over 65 (×100)	12.0	13.1	2.6	3.8	3.3	5.6
	(0.5)	(0.7)	(0.5)	(0.7)	(1.1)	(1.5)
Dummy for Just Under 65	Yes	Yes	Yes	Yes	Yes	Yes
Cubic Polynomial	No	Yes	No	Yes	No	Yes
	Weekend t-stat 2.54-6.62		Weekend t-stat 0.96-2.54		Weekend t-stat < 0.96	
	(7)	(8)	(9)	(10)	(11)	(12)
Age Over 65 (×100)	3.7	4.4	3.0	4.2	0.6	1.9
	(1.0)	(1.4)	(1.0)	(1.4)	(0.9)	(1.3)
Dummy for Just Under 65	Yes	Yes	Yes	Yes	Yes	Yes
Cubic Polynomial	No	Yes	No	Yes	No	Yes

Notes: See notes to Table 2. Standard errors in parentheses. Models include either a quadratic or cubic in age fully interacted with a dummy for over age 65 and a dummy for patients who are within 1 month of their 65th birthday. All models fit to 3,652 observations.

Appendix Table B: Regression Discontinuity Models for Charlson Comorbidity Score

	Dependent Variable = Charlson Comorbidity Score		
	(1)	(2)	(3)
Age Over 65 (×100)	0.011	0.027	0.028
	(0.019)	(0.016)	(0.022)
Additional Controls	No	Yes	Yes
Cubic Polynomial in Age	No	No	Yes

Notes: Standard errors in parentheses. Dependent variable is Charlson comorbidity score. Sample size for all models is 407,386. Mean of the dependent variable for patients age 64 is 1.90. All models also include a quadratic in age at admission fully interacted with dummy for age over 65. Models in columns 2 and 3 include the following additional controls: a dummy for people who are within 1 month of their 65th birthday, dummies for gender, race/ethnicity, month and year of admission and for Saturday or Sunday admission, and a complete set of unrestricted fixed effects for ICD-9 code of primary diagnosis. Model in column 3 includes a cubic in age at admission, fully interacted with dummy for age over 65.

Appendix Table C: Regression Discontinuity Models for Upper Quantiles and Standard Deviation of Treatment Intensity Measures

	Standard Deviation of Intensity Measure (1)	75th Percentile of Intensity Measure (2)	90th Percentile of Intensity Measure (3)
A. Length of Stay (in days)			
Age Over 65 (×100)	1.36	0.10	0.69
	(2.04)	(0.11)	(0.32)
B. Total Number of Procedures			
Age Over 65 (×100)	0.11	0.10	0.19
	(0.06)	(0.06)	(0.10)
C. Total List Charges (2002$)			
Age Over 65 (×100)	-1652	853	2139
	(4595)	(648)	(1754)
Implied Percentage Change at Age 65*	-2.3	2.2	2.6
	(6.4)	(1.7)	(2.2)

Notes: Standard errors in parentheses. Entries are estimated coefficients of dummy for age over 65 in regression discontinuity models fit to cell-level data for 3,562 cells representing ages at time of admission in days for patients age 60-70 admitted to California hospitals between January 1, 1992 and November 30, 2002. See Table 3 for additional details on sample. All models include a quadratic in age at admission, fully interacted with age over 65. Dependent variables in panel A are standard deviation and quantiles of length of stay for all patients admitted with a given age in days. Dependent variables in panel B are standard deviation and quantiles of the number of procedures for all patients admitted with a given age in days. Dependent variables in panel C are standard deviation and quantiles of total list charges (in 2002 dollars) for all patients admitted with a given age in days.

*Estimated discontinuity at age 65, divided by estimated mean for people just under age 65.

Appendix Table D: Regression Discontinuity Models for Specific Procedures for Patients Admitted with Two Leading Conditions

	Mean for Age 64-65	Coefficient of Dummy for Age≥65
	(1)	(2)
Principal Diagnosis = AMI		
Total Number of Procedures	5.0	0.4
		(0.1)
No Procedures Performed (%)	7.9	-1.9
		(0.8)
Incidence of Individual Procedures:		
Arteriography with 2 Catheters (%)	53.8	3.8
[88.56]		(1.5)
Left Heart Catheterization (%)	47.8	3.4
[37.22]		(1.6)
Angiocardiography of Left Heart (%)	45.5	4.0
[88.53]		(1.6)
Percutaneous Angioplasty (%)	29.0	0.7
[36.01]		(1.4)
Diagnostic Ultasound of Heart (%)	28.0	2.2
[88.72]		(1.4)

	Mean for Age 64-65	Coefficient of Dummy for Age≥65
	(3)	(4)
Principal Diagnosis = Chronic Obstructive Bronchitis		
Total Number of Procedures	1.2	0.0
		(0.1)
No Procedures Performed (%)	55.4	2.0
		(1.3)
Incidence of Individual Procedures:		
Medication by Nebulizer (%)	14.7	-2.2
[93.94]		(0.9)
Measurement of Blood Gases (%)	13.6	-0.1
[89.65]		(0.9)
Other Oxygen Enrichment (%)	8.1	-1.2
[93.96]		(0.7)
Electrocardiogram Monitoring (%)	7.0	0.9
[89.54]		(0.7)
Diagnostic Ultasound of Heart (%)	6.8	0.2
[88.72]		(0.7)

Notes: Table presents mean number of procedures or rates for various procedures (columns 1 and 3) and estimated regression discontinuities at age 65 (columns 2 and 4) from models with quadratic polynomial in age, fully interacted with dummy for age over 65. Models also include a dummy for age within 1 month of age 65, and dummies for gender and race/ethnicity. Standard errors in parentheses. Sample in columns 1-2 include 39,170 patients admitted for AMI (acute myocardial infarction). Sample in columns 3-4 includes 60,514 patients admitted for obstructive chronic bronchitis with acute exacerbation. See note to Table 3 for further restrictions on sample. Number in square brackets is ICD-9 procedure code.

Appendix Table E: Estimated Regression Discontinuity Models for Transfers and Readmission to Hospital

	Transferred Across Hospitals		Transferred Within Hospital	
	(1)	(2)	(3)	(4)
Age Over 65 (x100)	0.35	0.48	0.91	0.93
	(0.24)	(0.24)	(0.20)	(0.20)
Additional Controls	No	Yes	No	Yes
Mean for Patients Age 64 (x100)	6.87	6.87	4.02	4.02
	Readmitted Within 7 Days		Readmitted Within 28 Days	
	(5)	(6)	(7)	(8)
Age Over 65 (x100)	-0.36	-0.16	-0.92	-0.63
	(0.24)	(0.24)	(0.36)	(0.37)
Additional Controls	No	Yes	No	Yes
Mean for Patients Age 64 (x100)	6.59	6.59	17.02	17.02

Notes: Standard errors in parentheses. See notes to Table 4. Sample excludes patients with missing SSN's. Sample size for all models is 407,386.

Appendix Table F: Comparison of Linear Probability and Logit Specifications of Regression Discontinuity Model for Probability of Death

	No Additional Controls		With Additional Controls	
	OLS	Logit	OLS	Logit
	(1)	(2)	(3)	(4)
1. Death within 7 Days of Admission				
Dummy for Age≥65 (x100)	-1.1	-1.1	-1.1	-1.1
(mean rate at age 64 = 5.1%)	(0.2)	(0.2)	(0.2)	(0.2)
2. Death within 14 Days of Admission				
Dummy for Age≥65 (x100)	-1.0	-1.0	-1.0	-1.0
(mean rate at age 64 = 7.1%)	(0.2)	(0.2)	(0.3)	(0.3)
3. Death within 28 Days of Admission				
Dummy for Age≥65 (x100)	-1.1	-1.1	-1.0	-1.0
(mean rate at age 64 = 9.8%)	(0.3)	(0.3)	(0.3)	(0.3)
4. Death within 90 Days of Admission				
Dummy for Age≥65 (x100)	-1.1	-1.1	-1.0	-1.0
(mean rate at age 64 = 14.7%)	(0.3)	(0.3)	(0.3)	(0.4)
5. Death within 180 Days of Admission				
Dummy for Age≥65 (x100)	-1.2	-1.2	-1.1	-1.0
(mean rate at age 64 = 18.4%)	(0.4)	(0.4)	(0.4)	(0.4)
6. Death within 365 Days of Admission				
Dummy for Age≥65 (x100)	-1.0	-1.0	-0.9	-0.8
(mean rate at age 64 = 23.0%)	(0.4)	(0.4)	(0.4)	(0.4)

Notes: Standard errors in parentheses. Logit coefficients are marginal effects from estimated logit models. All models include quadratic in age in days at admission, fully interacted with dummy for age over 65. Models in columns 3 and 4 also include the following controls: dummies for year and month of admission and admission on Saturday or Sunday, dummies for gender and race/ethnicity, and a dummy for admissions in the month prior to reaching age 65. Sample size for all models is 407,386.