NBER WORKING PAPER SERIES

DOES MEDICARE SAVE LIVES?

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Working Paper 13668
http://www.nber.org/papers/w13668

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2007

We thank the California Department of Health Services for providing us with the data used in the paper. This research was supported by a grant from the National Institute for Aging. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 13668
November 2007
JEL No. H51,I11

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 room for "non-deferrable" conditions -- diagnoses with the same daily admission rates on weekends and weekdays. Among this subset of patients there is no discernible 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 much 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 significant increases in hospital list chargers, in the number of procedures performed in hospital, and in the rate that patients are transferred to other care units in the 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 two years 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 room for "non-deferrable" conditions – those with similar weekend and weekday admission rates. We argue that the decision to present at an emergency room 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 room 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 diagnosis mix 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 similar rise in total list charges. We also find a relatively large increase in the likelihood that patients are transferred to other units within the same hospital (mainly skilled nursing facilities) and a reduction in the 28-day readmission rate. Finally, 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 28 days and 90 days, and persists for at least two years after admission, suggesting that the differential treatment afforded to those with Medicare coverage has an important long-run impact on patient survival.

We conclude by discussing potential channels for the Medicare effect. One possibility is that it reflects changes in treatment intensity and mortality for the small fraction (<10%) of patients who move from uninsured to insured status once Medicare is available. In fact, the magnitude of our estimated mortality effect is too large (and too widely distributed) to be driven entirely by this group. We argue that a more plausible channel is the easing of case review procedures and other restrictions as patients who were previously covered by private insurance or Medicaid become Medicare-eligible at 65.

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 room 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

a. Medicare Eligibility and Health Insurance

Medicare is provided to people who are 65 or older and have worked at least 10 years in covered employment.[1] 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.[2] Age-eligible individuals can enroll on the first day of the 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. Figure 1 illustrates the transition using 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.

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[1] 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

The fraction of people with Medicare coverage rises by about 60 percentage points at age 65.[3] Apart from this, the age profile is relatively smooth and well-described by a simple quadratic function. Associated with the rise in Medicare coverage 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.

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%, as many of those with privately insurance before 65 obtain a supplemental policy to "top up" their Medicare coverage.[4] Conversely, the fraction of people covered by managed care in their primary policy falls by 30%. 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 choose managed care over traditional fee-for-service insurance.[5]

To summarize, 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, nearly 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

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[2] 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.

[3] Other data sources (e.g., the Survey of Income and Program Participation and the Current Population Survey, show somewhat higher Medicare enrollment after age 65. We suspect that at least some of the over-65 respondents in the NHIS who do not report Medicare are actually covered. It is widely believed that the participation rate in Medicare Part A by people eligible for the program is close to 100% (Remler and Glied, 2003).

[4] 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.

[5] 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.

multiple-coverage. And, since most Medicare recipients choose traditional fee-for-service coverage, the fraction of the population with managed care is cut in half.

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) 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 (2007) 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.[6] Most existing studies have

[6] 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.

focused on mortality as an indicator of health.[7] 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 1963. Neither exercise suggests that the introduction of Medicare reduced the relative mortality of people over 65.

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 room for relatively severe illnesses. Any extra services offered to the Medicare-eligible subset of this population have at least a plausible chance of affecting short run mortality. By comparison,

[7] 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.

Medicare-induced services would have to have a very large impact on mortality to generate a detectable effect on a relatively healthy population.[8]

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), f( ) is a function that is continuous at age 65 with parameters 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 other factors. 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).[9] 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 <u>any</u> health insurance; (2) an effect driven by people

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[8] 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 detect a statistically significant effect in a one-year follow-up, even with 100,000 observations in each group. The reason for the low power is that the baseline mortality rate of 65 year olds is only about 1.5% per year.

switching from an insurance carrier other than Medicare to a package that includes Medicare;[10] (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.

As emphasized by Lee (2007), 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 implies

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

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, 2007) this is a serious threat to an RD analysis of the health outcomes of patients. Figure 2 illustrates the difficulty 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

[9] 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.

number of non-Emergency Room admissions jumps by approximately 12%, while the number of Emergency Room admissions rises by 3%. Assuming that the additional patients are not as sick as those who would enter 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 room (ER) for a relatively severe set of conditions that require immediate hospitalization. Specifically, we identify a set of admission diagnosis codes with similar ER admission rates on weekdays and weekends.[11] 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

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[10] 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.

[11] 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.

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 Appendix Figure A, recent data show no discontinuity in the likelihood of working at exactly age 65.[12] 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 ER for non-deferrable conditions.

[12] 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.

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 room do not appear in the sample.[13] As explained in the Data Appendix (available on request), we drop discharge records for patients admitted before January 1, 1992, or on or after December 1, 2002, to avoid length-biased sampling problems.

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 (which we call the "admission diagnosis"), whether the admission was planned or unplanned, the route into the hospital (ER versus non-ER), 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 within or between hospitals, 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 that we merge with the initial discharge file in order to determine the date of death for patients in the sample.

One notable data issue 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 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 unplanned admission rates through the ER on weekdays and weekends. Arguably, these diagnoses are "non-deferrable," and patients with these conditions will present at the ER at the same rate just before and just after their 65th birthday, irrespective of Medicare coverage.

Figure 3 shows how the distribution of the fraction of weekend admissions for different diagnosis codes changes as we focus on more restrictive subsets of admissions. The density for all admission diagnoses is centered on 0.24, far below the 2/7=0.29 rate expected if admissions were equally likely on weekends and weekdays. Clearly, there are many ICD-9 codes with lower admission rates on the weekend than during the week. The density for the subset of emergency admissions has a mode near 2/7 but is still skewed to the left, suggesting that even among ER admissions there are many diagnoses with an under-representation of weekend admits. Finally, the spiked density in Figure 3 shows the distribution of the fraction of weekend admits among unplanned ER admits, limiting the set of ICD-9 codes to those for which the t-statistic for a test of similar weekend and weekday admission rate (i.e., the fraction of weekend admits= 2/7) is less than 0.965. This distribution is tightly centered around 2/7.

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

Table 1 summarizes the 10 most common admission diagnoses codes in this subsample of 425,315 "non-deferrable" admissions. The largest diagnosis category is obstructive chronic bronchitis with acute exacerbation. (This includes chronic bronchitis with emphysema, known as "chronic obstructive pulmonary disease" – a common diagnosis for smokers and ex-smokers). Patients with this condition have an average hospital stay of 6.23 days, an average of 1.21 procedures performed during their stay, and a 4.7% 28-day mortality rate. Most of the other relatively common admission codes result in even longer stays, more procedures, and a higher death rate. On average, it appears that diagnoses with the same admission rates on weekdays and the weekend are extremely acute and often life-threatening.

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 (2007), though we have a discrete running variable (age, measured in days) and we use a parametric rather than a non-parametric approach. Figure 4 shows the age profiles of the log of the daily admission count for four groups of ER admissions, based on the magnitude of the t-statistic for the test of a constant weekday/weekend admission rate. 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 of the 6 panels in this table presents two different RD specifications for the log of the number of admissions by age (in days) of the admitted patient. We focus on 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 Appendix Table B).

A limitation of our data set is that although we know each patient's age in days at the time of admission, we do not know birthdates or exact admission dates.[14] 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. Appendix Figure C 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 second specification reported in each panel of Table 2 includes a dummy for these observations. The addition of this dummy has relatively little impact on the estimated coefficients.[15] Looking at the first two panels, we estimate that non-ER and planned ER admissions rise by about 12% at 65, while unplanned ER admissions rise by 2.5%. The remaining four panels report the results for the four quartiles of unplanned ER admissions shown in Figure 4. As suggested by the graph, the estimated models show no discernable rise in admissions for our preferred subgroup of diagnoses with the lowest t-statistic for the comparison between weekday and weekend admission rates.

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

We have also checked for discontinuities in the case mix and demographic composition of the non-deferrable subsample at age 65. 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 admission 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 mortality characteristics shift at age 65. The results for 7-day and 28-day predicted mortality are shown in Appendix Figure D. (Results for other windows are very similar and are available on request). The age profiles of predicted probability 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. In light of these testing results, we proceed under the assumption that patient health in the non-deferrable subsample trends smoothly at age 65.

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

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 5 shows the age profiles of the fractions of people with various primary insurers (private, Medicaid, Medicare, other, and none)

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[15] The bottom row of each sub-panel shows the p-value for a test that this additional variable has no effect. In all six

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 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. This table has the same format as 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 in columns 2 and 3 of each panel. For reference, the specification in the first column excludes these controls and also excludes the dummy for admissions in the 31 days before a patient's 65th birthday.[16]

The regression results confirm the visual impressions conveyed in Figure 5. 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.[17] 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 fraction 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% in the nondeferrable subsample, versus -9.5% 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.

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panels the p-value is well above the usual critical value.

[16] As in Table 2, the bottom row of each sub-panel shows the p-value for a test of joint significance of the additional variables included in the specification in column 2 (relative to column 1) and in column 4 (relative to column 3).

[17] 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.

b. Services

We have three basic measures of patient services: length of stay, number of procedures performed, and total hospital list charges.[18] Figure 6 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 only marginally 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 3 percent (with a t-ratio of around 3). These increases, although modest in size, are consistent with the findings in earlier work, and confirm that the onset of Medicare eligibility leads to increased use of medical services. Importantly, we are finding these increases for a sample of acutely ill patients arriving at the hospital for emergency treatment, rather than for elective procedures (as in Card, Dobkin, and Maestas, 2007) or preventive care screenings (as in Decker and Rapaport, 2002, or McWilliams et al., 2003).

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 5. Looking first at AMI, 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

[18] 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

increases of about 4% in the use of several important diagnostic procedures, including coronary arteriography, cardiac catheterization, and angiocardiography.[19] 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 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.

c. Transfers

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).[20] Because our data are derived from hospital discharge records, we cannot measure transfers to stand-alone skilled nursing facilities (SNF's) or to other care options that may be substitutable with post-acute care in a hospital setting. Nevertheless, it is interesting to ask whether Medicare eligibility is associated with any change in the likelihood of patient transfer to other care units in the same hospital, or to a second hospital.

Figure 7 shows the age profiles of these two outcomes. Both within- and between-

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charges for physician services, and are not reported for patients at Kaiser-run hospitals. We interpret list charges as a convenient "price-weighted" summary of services rendered, albeit at somewhat artificial prices.

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

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

hospital transfer rates rise at age 65, with a particularly large rise in within-hospital transfers. Corresponding RD regression models are presented in the upper panel of Table 6, and confirm that the within-hospital transfer rate rises by about 1 percentage point (on a base level of about 4% among 64 year olds) once patients are over 65.

Further analysis (not shown) indicates that the rise in within-hospital transfers at 65 is driven by a jump in the transfer rate to skilled nursing facilities (SNF's) in the same hospital. Until 1998, post-acute care delivered in skilled nursing facilities, rehabilitation units, and home health care agencies was reimbursed on a cost-basis, whereas acute care was covered by prospective payments (Cotterill and Gage, 2002). Newhouse (1996, 2002) argues that the more generous reimbursement system for post-acute care contributed to the rapid growth in SNF's (both within hospitals and in free-standing units), and to a relatively high rate of transfer of Medicare patients to SNF's following their initial hospitalization. The discontinuity in within-hospital transfers at age 65 is consistent with this argument.

Medicare reimbursement for post-acute care was switched to a prospective payment system in 1998, leading to a sharp reversal in the growth rate of hospital-based SNF's (Dalton and Howard, 2002). To check whether this change led to a shift in the transfer rate of Medicare patients to hospital-based SNF's, we estimated separate RD models for within- and between-hospital transfers for 1992-98 period and the 1999-2002 period. Although the RD in between hospital transfers is essentially the same in the two period, the RD in within-hospital rates falls substantially, from 1.2 percentage points in the pre-1998 period (standard error 0.3) to 0.6 percentage points in the post-1998 period (standard error 0.3). This provides further confirmation that hospitals were responding to the payment incentives in the pre-1998 system by transferring patients to hospital-based SNF's, and that the elimination of these incentives led to reduced use of hospital-based SNF's for Medicare patients.

Finally, Figure 8 and the RD models in the lower panel of Table 6 address the likelihood that a patient is re-admitted to the hospital (after at least 1 day out of the hospital). This outcome could be interpreted as a measure of the "quality" of treatment in the initial hospital stay, although this interpretation is clouded by the impact of Medicare eligibility on mortality (since people who die cannot be readmitted). We focus on re-admission within 7 and 28 days of discharge. The figures suggest that the readmission rate after 7 days is relatively flat through the age 65 threshold, while the readmission rate after 28 days drops significantly. The RD models suggest that the 28-day readmission rate is about 0.6% lower for people just over 65, though the sampling error is relatively large. We return to discuss this impact in more detail after we have presented the mortality impacts in the next subsection.

d. Mortality

Figure 9 plots the age profiles for the probability of death within 7, 14, 28, 90, 180, and 365 days of admission to the hospital, while Table 7 presents estimates from the RD regression models corresponding to each of these outcomes. Inspection of Figure 9 shows that each of the mortality measures shows a drop on the order of 1 percentage point at age 65. The regression estimates in Table 7 confirm this: we observe a reduction in 7-day mortality of about 1 percentage point 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. Figure 10 shows the estimated post-65 coefficients from RD regression models at all possible follow-up windows from 1 day to 2 years, along with the associated 95% confidence intervals.[21] The estimated mortality effect of Medicare eligibility on our sample of non-deferrable admissions is relatively stable at about 1 percentage point over the entire range of follow-up periods.

Our estimate of the mortality effect of Medicare eligibility is relatively large: it represents a 20% reduction in 7-day mortality, a 9% reduction in 28-day mortality, and a 3-4% reduction in 1-year mortality relative to death rates among 64 year olds with similar conditions at admission. The fact that the effect emerges within 7 days and persists for two years suggests that the extra services or changes in the quality of services provided to Medicare-eligible admittees have an immediate life-saving effect, and lead to a significant gain in the duration of life.

It is worth noting that the mortality reductions estimated in Table 7 appear to reflect changes in the treatment of patients with Medicare within the same hospital, rather than patient sorting to higher-quality hospitals at 65. The fractions of patients 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 of non-deferrable admissions 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 that such a small shift in patients out of these hospitals could have much affect on average mortality.[22] Thus, it does not appear that Medicare reduces mortality by shifting patients to better hospitals.

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[21] These estimates are from our base specification with no additional controls (i.e., the first specification in each panel of Table 7).

[22] 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.

In view of the relatively large mortality effects associated with Medicare eligibility, it is worth re-considering the estimated impacts on hospital re-admission rates. A re-admission at some time interval (say 28 days) can only be observed if the patient is still alive: i.e.,

P(re-admission) = P(re-admission|alive) × P(alive).

At age 64, the average 28-day death rate for our sample of non-deferrable patients is 9.8%, while the *unconditional* re-admission rate after 28 days is 17.1%. This implies that the re-admission rate for people just under 64, conditional on being alive after 28 days, is 18.96%. Our estimated RD models show a drop in the unconditional readmission rate of -0.63% (Table 6, 4th panel. specification (3)), and a drop in the mortality rate of -0.9% (Table 7, 3rd panel, specification (3)). Adding these to the base rates at age 64, the conditional re-admission rate for living patients rises to 18.08% at age 65. Thus, correcting for the bias caused by mortality, the implied effect of Medicare eligibility on the 28-day conditional re-admission rate is -0.88% -- 40% larger (in absolute value) than the impact on the unconditional re-admission rate. This is a relatively large impact and suggests that Medicare eligibility not only reduces mortality but also morbidity among surviving patients.

e. Robustness of Mortality Estimates

To further probe our estimated mortality effects we used a simple bounding procedure to obtain <u>lower-bound</u> 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 who are 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:

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

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

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

Table 8 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 room, or for a planned hospitalization (which we call "elective" admissions, in column 2); those who enter via the ER for an unplanned hospitalization (column 3); and the four subgroups of the unplanned-ER group, based on admission diagnoses with different ranges of weekend versus weekday admissions (i.e., the four subgroups graphed in Figure 4) in columns 4-7. The first row of Table 8 presents the estimated RD in the log of the number of hospital admissions at age 65, which is an estimate of $\alpha/(1-\alpha)$.[23] 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 a RD model with an interacted quadratic function of age fit to aggregated mortality rates by age in days.[24] 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 admission 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

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[23] 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 $\alpha/(1-\alpha)$.

[24] 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

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 ways. First, it proves there is no mechanical data problem that is causing us to measure lower death rates for all patients over 65.[25] 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, a negative effect on re-admission rates, 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

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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.

[25] 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

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 characteristics at age 65. Suppose that health care services delivered to patient i, (S_i) depend on age, an error term υ_{si}, and the characteristics of the insurance package:[26]

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

Finally, assume the likelihood of death of patient i (y_i=1) depends on age and on 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 k^{th} element of z_i contributes $\theta_k \, \pi_k$ to the RD in services and $\lambda \, \theta_k \, \pi_k$ to the RD in

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

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 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). 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 none 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.[27] 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

[26] 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).

[27] 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 λ

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. (Results are available on request). We do find significant increases in the numbers of procedures and significant reductions in mortality even for patients from the high-insurance zip codes (who have only a very small gain in the probability of insurance coverage at age 65), suggesting that a increase in insurance coverage per se is not the explanation for the impacts of Medicare.

Instead, we suspect that the measured mortality effects arise because Medicare imposes fewer restrictions than private insurance or Medicaid, leading to more (and possibly higher-quality) services to Medicare patients. This interpretation is similar to the conclusion reached in Card, Dobkin, and Maestas (2007), where we note that Medicare eligibility leads to increases in hospitalization rates for a wide range of procedures, with bigger increases for whites than blacks or Hispanics, even though whites tend to have higher rates of insurance coverage prior to age 65.

VII. Summary and Conclusions

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 room with diagnoses that have

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$\theta'\pi(g)$. By comparing the relative sizes of the discontinuities in insurance, treatment intensity, and mortality across 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 several measures of treatment intensity at age 65, including the number of procedures performed in hospital, total list charges, and the likelihood of transfer to other care units in the hospital. Associated with these changes we find relatively large reductions in patient mortality at age 65. Medicare eligibility reduces 7-day mortality by about 1 percentage point, with similar sized reductions at 14 days, 28 days, 90 days, and through the end of our follow-up period. 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. Instead, our findings point to a more widespread effect of Medicare on treatment intensity and mortality, including patients who were insured prior to 65. We argue that this pattern is consistent with an "insurance generosity"

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subgroups it is possible to judge whether the data are consistent with a "1-channel" explanation.

channel, reflecting increased services (or the more timely delivery of services) for patients who are covered by Medicare and supplemental insurance relative to the typical insurance package held by people just under 65.

Finally, it is worth noting that the reduction in mortality is achieved with only a modest rise in hospital list charges (around 4%). This is an incomplete measure of the total cost increase associated with Medicare eligibility because it excludes doctor bills and charges for other non-hospital personnel. If these unobserved costs also rose by 4% we suspect that the implied cost-benefit analysis for making Medicare available to people admitted for non-deferrable conditions would be very favorable. However, Medicare eligibility also leads to large increases in the use of services by other, less sick, patients for whom the effects on mortality are very small, or even zero. Whether the overall cost of the system is justified by the gains in health therefore remains an important issue for further research.

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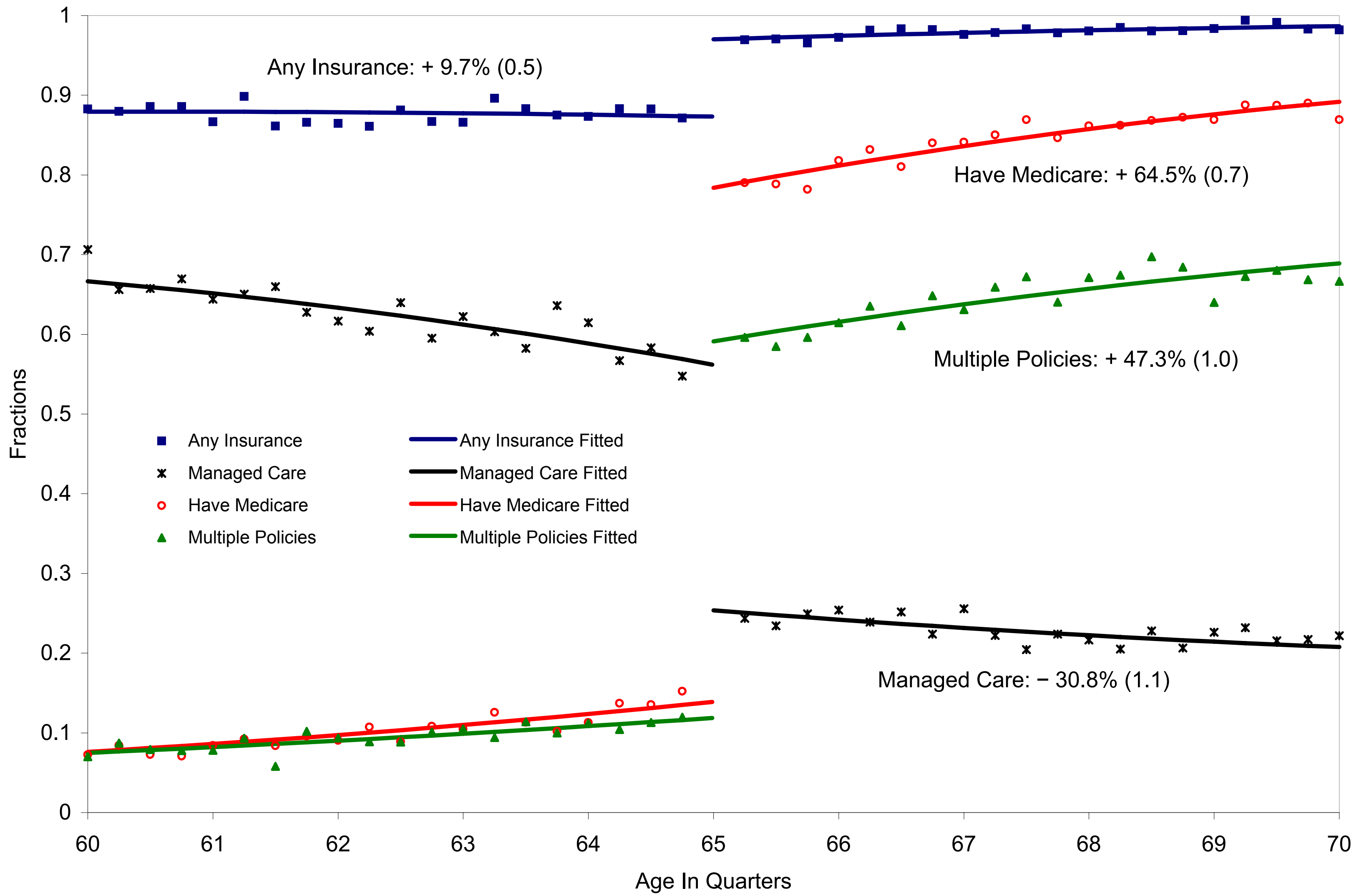
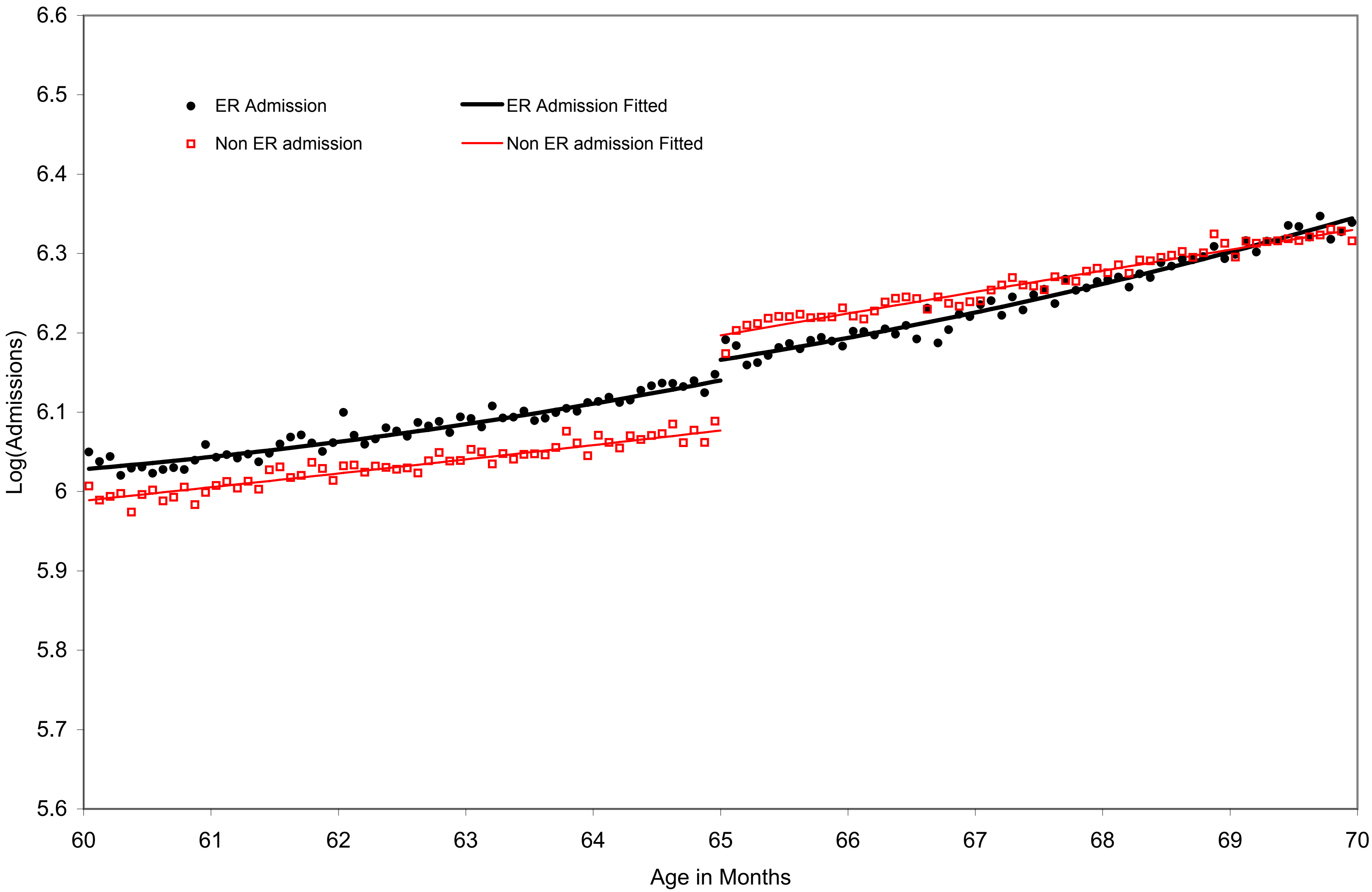
Figure 1: Changes in Health Insurance at Age 65, National Health Interview Data



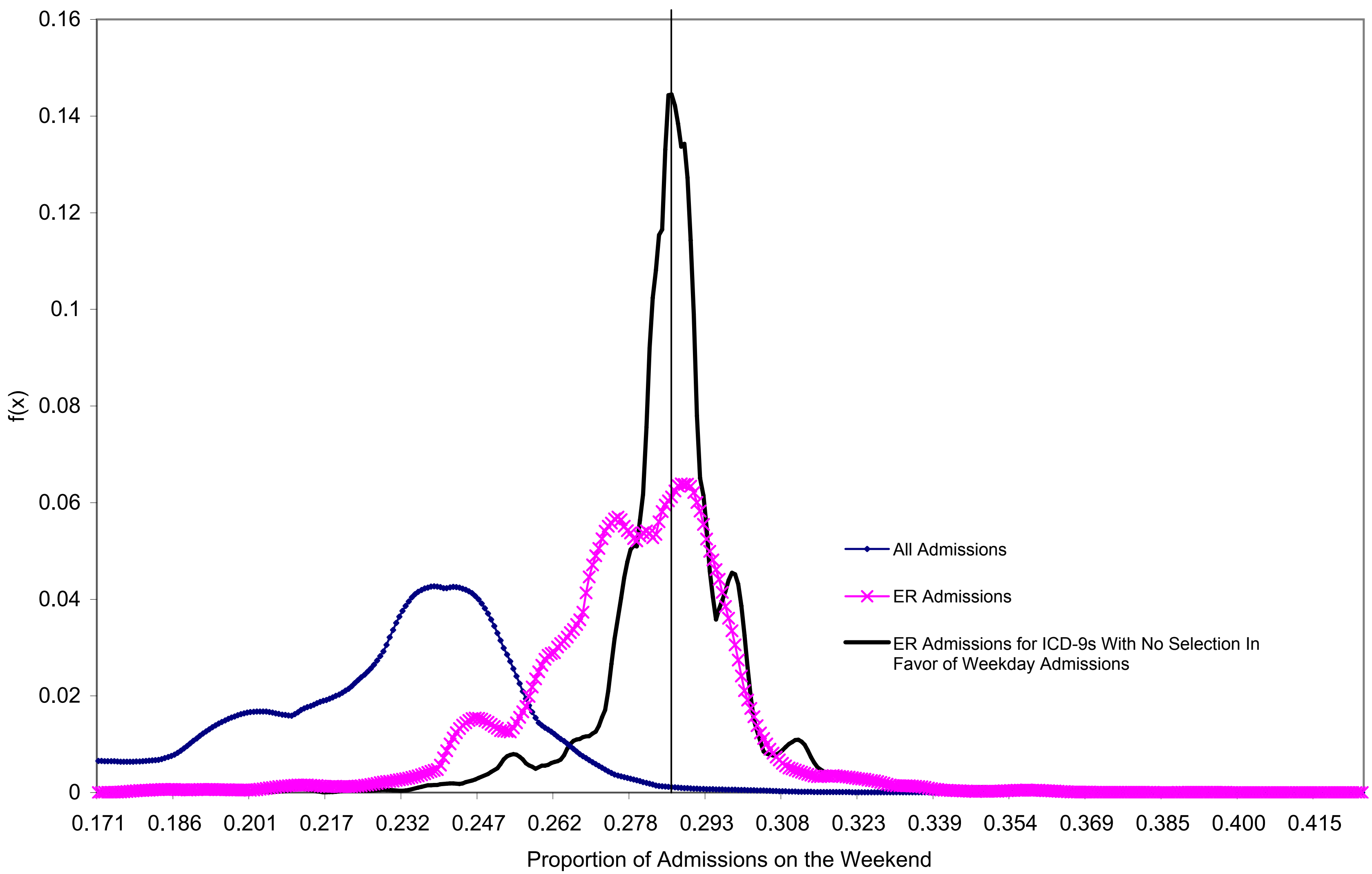
Notes: Estimated discontinuities (and standard errors) at age 65 from fully interacted quadratic shown. Models include dummy for uncertainty of eligibily status of people assigned to age=65.0. This point has been dropped from the figure.

Figure 2: Hospital Admission by Route of Admission (California 1992-2002)



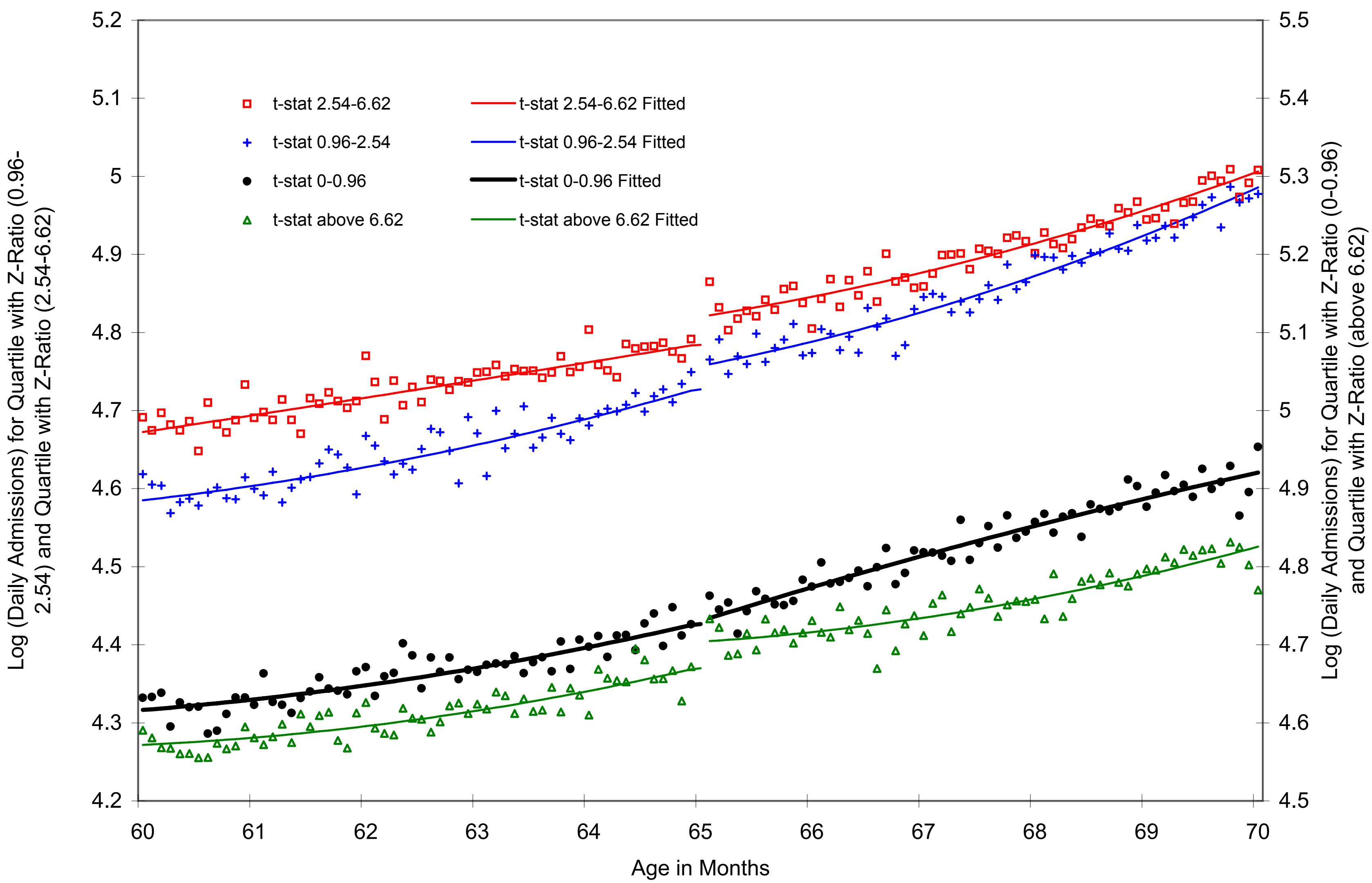
Notes: The points are the log of the average admission count. The fitted values are from regressions that include a second order polynomial in age fully interacted with a dummy for age >= 65 and a dummy variable for the month before people turn 65.

Figure 3: Proportion of Admissions that Occur on the Weekend by ICD-9



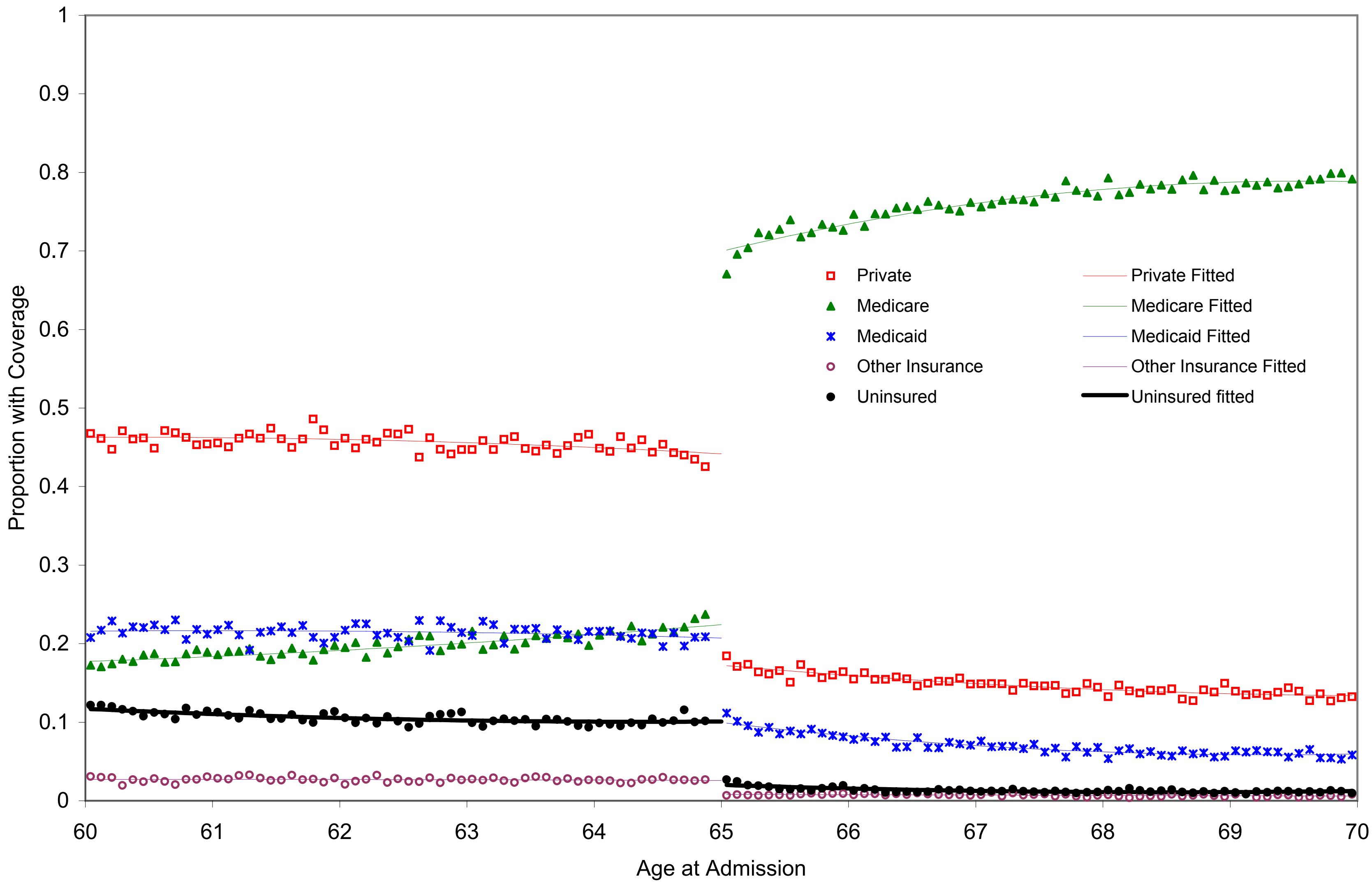
Notes: To create the figures above we computed the proportion of patients admitted on the weekend for each ICD-9. We then computed the KDE of the weekend admissions proportions over the ICD-9s. We repeated the process for admissions through the ER.

Figure 4: Admission Through the ER by Quartile of Weekend Proportion of ICD-9



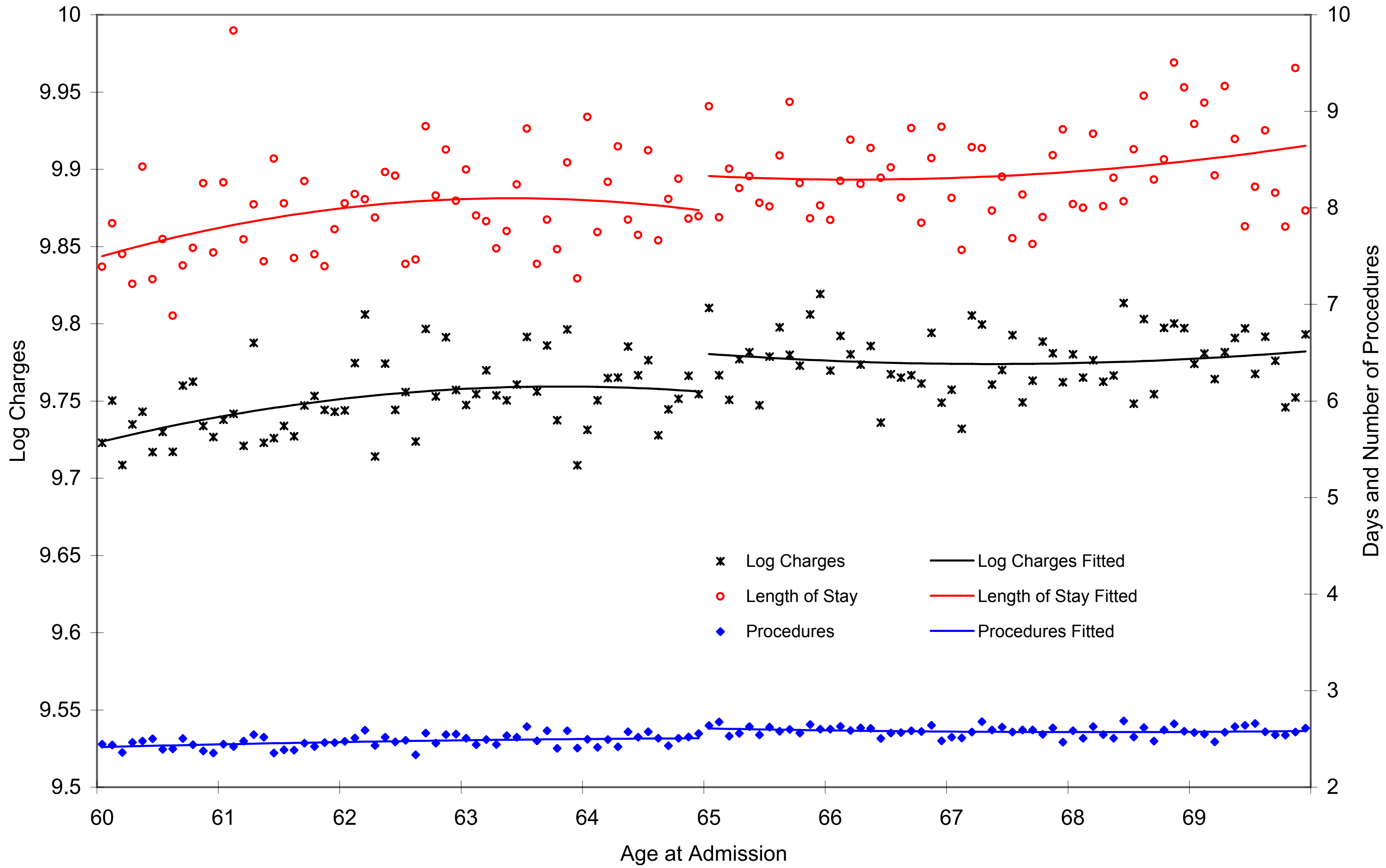
Notes: See notes from Figure 2. For the sample of ER admissions the age profiles above are created by computing the t-statistic for the test that an ICD-9 has a weekend to weekday ratio of 2:5. The admissions into quartiles based on the t-statistic.

Figure 5: Primary Insurance Coverage



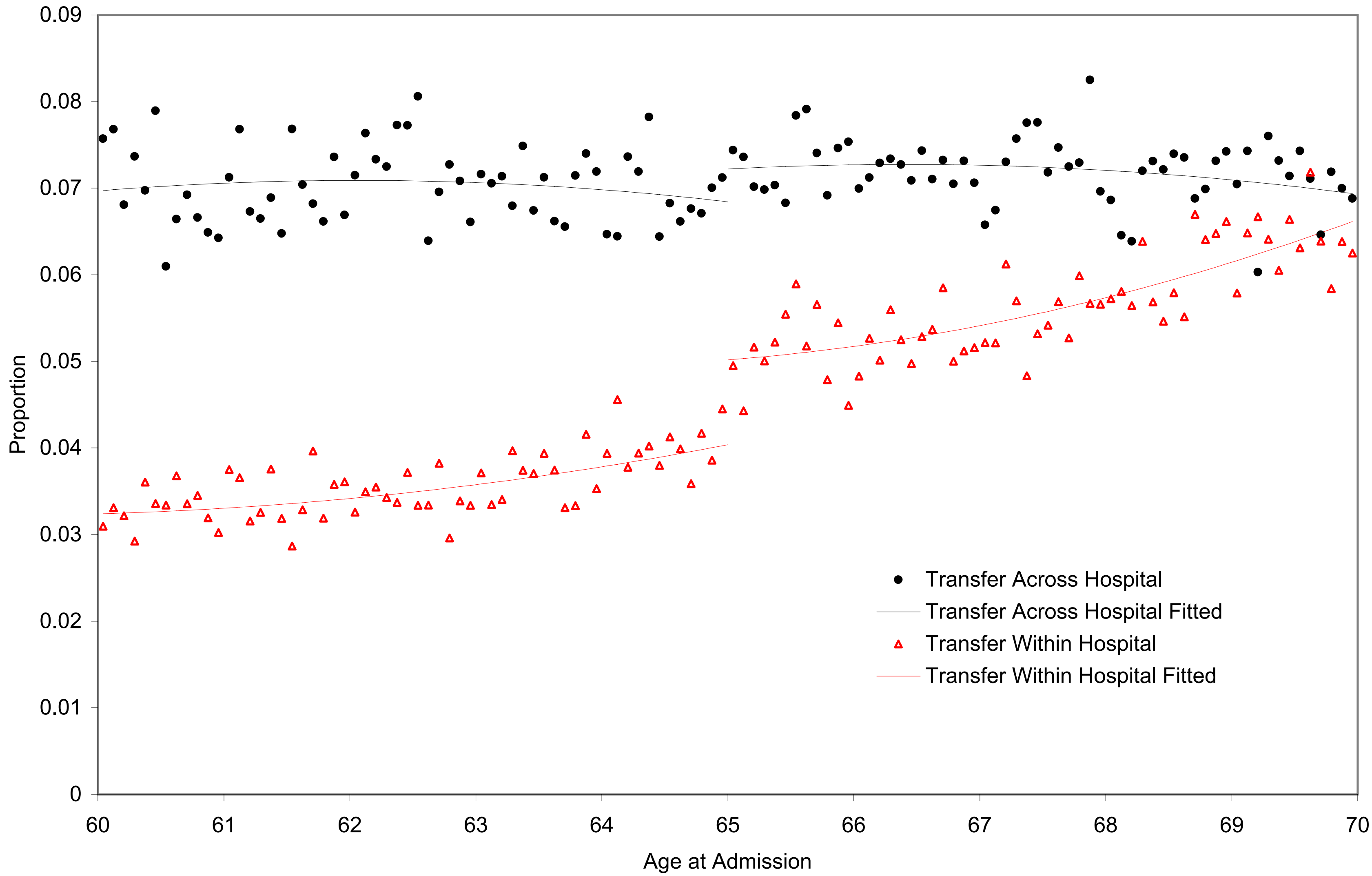
Notes: Coverage is the expected primary payers. These figures are derived from the 425,315 admissions that show no evidence of selection.

Figure 6: Three Measures of Within Hospital Treatment Intensity



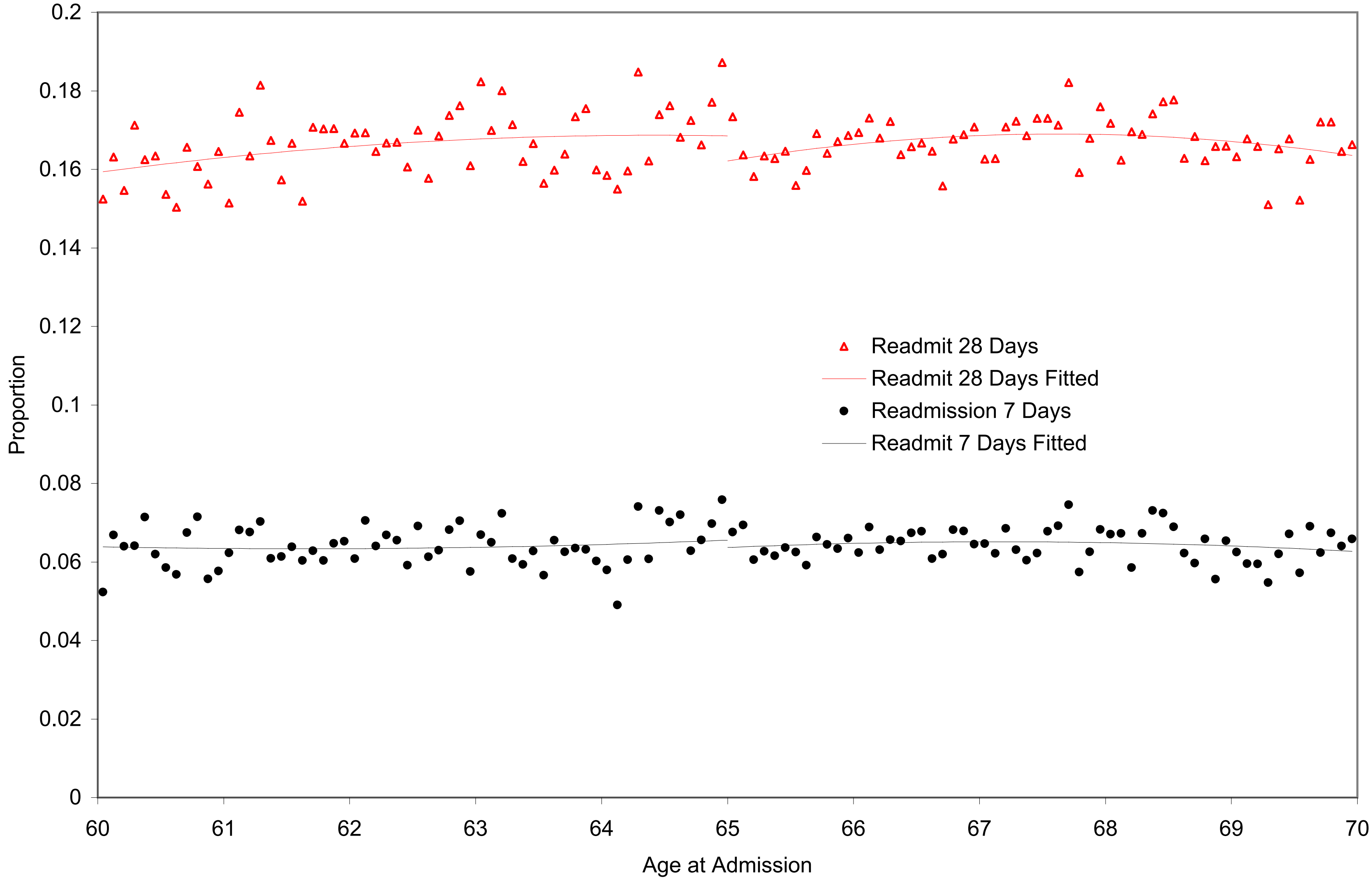
Notes: See notes from Figure 2. Charges are unavailable for 13.4% of the sample. At age 65 there is a discrete 0.6% decrease in the number of records where charges are unavailable. Individuals without a SSN have been dropped.

Figure 7: Transfer After Admission to the Hospital



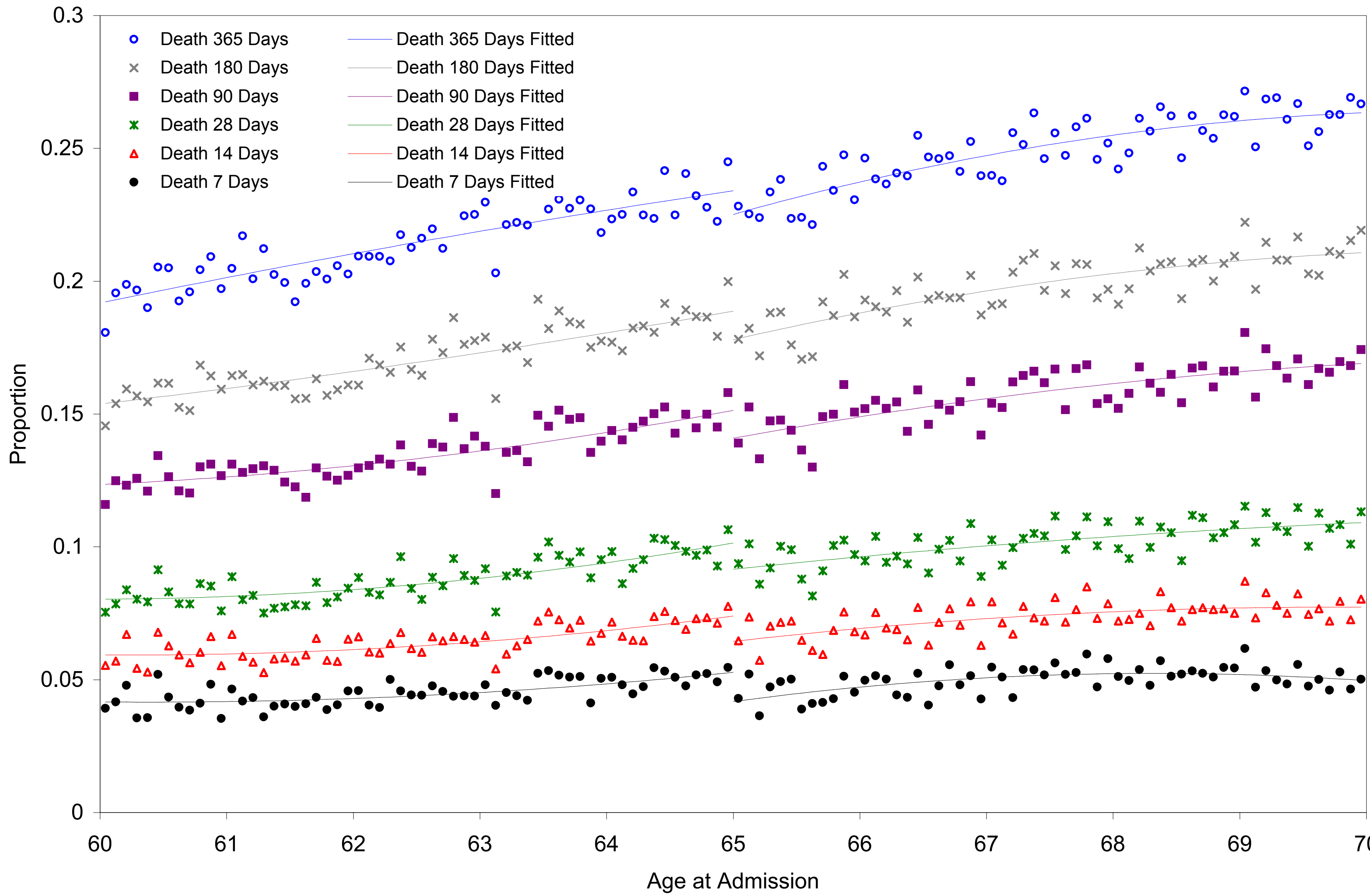
Notes: Inidividuals without SSNs are not included in the figure as they can't be tracked.

Figure 8: Readmitted to Hospital



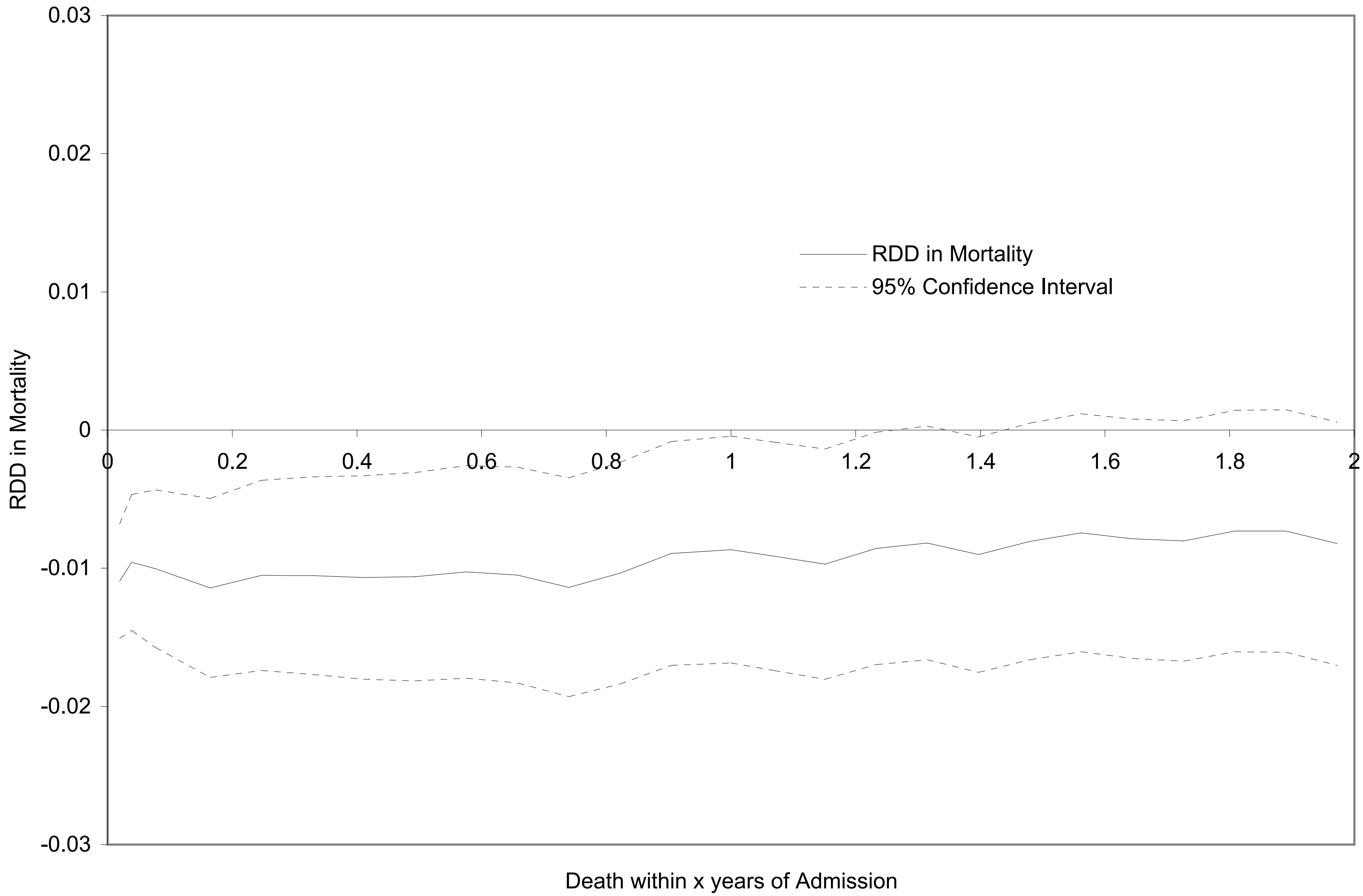
Notes: See notes from Figure 5. Days to readmission are computed from date of discharge. Individuals without a SSN have been dropped.

Figure 9: Died Either in or Out of Hospital



Notes: See notes from Figure 5. These deaths are coded based on death certificate data. They are linked to the hospital records based on SSN. Records without SSNs were dropped.

Figure 10: RDD in Mortality for the Three years After Hospital Admission



Notes: Evolution of RDD and 95 percent confidence interval. Due to how the datasets were merged there is substantial censoring of deaths occurring more than 2 years after admission.

Table 1: Ten Most Common ICD-9s in Non-deferrable Admission Sample

	ICD-9	Admissions	Length of Stay	Procedures	List Charges	Transfer Across Hospital	Died within 28 Days
Obstructive chronic bronchitis with acute exacerbation	491.21	61,558	6.23	1.21	23,835	2.8	4.7
Respiratory failure	518.81	24,328	13.67	3.70	65,459	9.5	22.5
Acute myocardial infarction of other inferior wall first episode	410.41	21,192	7.23	5.13	52,798	26.0	6.9
Acute myocardial infarction of other anterior wall first episode	410.11	15,727	7.82	5.31	56,684	24.6	10.6
Intracerebral hemorrhage	431	10,755	17.77	3.63	61,870	15.0	29.6
Chronic airway obstruction, not elsewhere classified	496	9,102	6.46	1.47	18,868	3.1	7.7
Fracture of neck of femur Intertrochanteric section	820.21	6,868	14.15	2.66	39,614	9.8	2.9
Cerebral artery occlusion, unspecified	434.9	5,782	15.15	3.68	26,863	14.1	8.1
Convulsions unknown Cause	780.39	5,338	5.13	1.25	21,850	4.2	3.1
Asthma, unspecified with status asthmaticus	493.91	5,095	4.61	1.09	15,651	1.7	0.9

Note: Length of stay, procedure count and hospital list charges are totals for all sequential hospital stays.

Table 2: Changes in Admissions at Age 65 for California Hospital Admissions 1992-2002

	Non ER or Planned		ER and Unplanned	
Age Over 65 (x100)	11.9	12.0	2.4	2.6
	[0.5]	[0.5]	[0.5]	[0.5]
Dummy Just Under 65	N	Y	N	Y
Observations	3,652	3,652	3,652	3,652
R-Squared	0.87	0.87	0.81	0.81
P-Value		0.16		0.28
	Weekend t-stat > 6.62		Weekend t-stat 2.54-6.62	
Age Over 65 (x100)	3.2	3.3	3.6	3.7
	[1.0]	[1.1]	[0.9]	[1.0]
Dummy Just Under 65	N	Y	N	Y
Observations	3,652	3,652	3,652	3,652
R-Squared	0.39	0.39	0.54	0.54
P-Value		0.76		0.56
	Weekend t-stat 0.96-2.54		Weekend t-stat < 0.96	
Age Over 65 (x100)	2.7	3.0	0.6	0.6
	[0.9]	[1.0]	[0.9]	[0.9]
Dummy Just Under 65	N	Y	N	Y
Observations	3,652	3,652	3,652	3,652
R-Squared	0.63	0.63	0.52	0.52
P-Value		0.20		0.85

Notes: Standard errors in square brackets. Table reports coefficient estimates from models fit to data on log number of admissions by single day of age. Sample is restricted to people admitted from home to California hospitals between January 1, 1992 and November 30, 2002. All models include a quadratic polynomial in age, fully interacted with a dummy for age over 65. Dummy for just under 65 is set to 1 for people admitted in the 31 days before their 65th birthday. P-values reported in column 2 of each sub-panel are for the test that the coefficient of the dummy for just under 65 is equal to zero.

Table 3: Regression Discontinuity Estimates of Changes in Insurance Coverage

	Medicare				Uninsured			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Age Over 65 (x100)	43.9	47.6	47.5	45.8	-7.4	-8.1	-8.0	-7.9
	[0.4]	[0.4]	[0.4]	[0.6]	[0.2]	[0.2]	[0.2]	[0.3]
Year/Month/Sat/Sun	N	Y	Y	Y	N	Y	Y	Y
Race and Gender	N	Y	Y	Y	N	Y	Y	Y
Dummy Just Under 65	N	Y	Y	Y	N	Y	Y	Y
Condition FE	N	N	Y	Y	N	N	Y	Y
Cubic Polynomial	N	N	N	Y	N	N	N	Y
Mean Age 64-65 (x100)	24.0	24.0	24.0	24.0	9.7	9.7	9.7	9.7
Observations	425,315	425,315	425,315	425,315	425,315	425,315	425,315	425,315
P-Value		0.00		0.00		0.00		0.00

	Private				Medicaid			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Age Over 65 (x100)	-24.8	-26.9	-26.8	-26.0	-10.1	-10.9	-10.8	-9.8
	[0.4]	[0.4]	[0.4]	[0.6]	[0.3]	[0.3]	[0.3]	[0.35]
Year/Month/Sat/Sun	N	Y	Y	Y	N	Y	Y	Y
Race and Gender	N	Y	Y	Y	N	Y	Y	Y
Dummy Just Under 65	N	Y	Y	Y	N	Y	Y	Y
Condition FE	N	N	Y	Y	N	N	Y	Y
Cubic Polynomial	N	N	N	Y	N	N	N	Y
Mean Age 64-65 (x100)	43.3	43.3	43.3	43.3	20.5	20.5	20.5	20.5
Observations	425,315	425,315	425,315	425,315	425,315	425,315	425,315	425,315
P-Value		0.00		0.15		0.00		0.00

Notes: Standard errors in square brackets. Table reports coefficient estimates from linear probability models fit to data on sample of people admitted from home to California hospitals between January 1, 1992 and November 30, 2002. All models include a quadratic polynomial in age, fully interacted with a dummy for age over 65. Dummy for just under 65 is set to 1 for people admitted to the hospital in the 31 days before their 65th birthday. Race and gender represent dummies for race/ethnicity and gender. Condition FE represents a set of fixed effects for primary admission diagnosis. Mean age 64-65 represents the mean of dependent variable among people with 64<= age<65. P-values reported in column 2 of each sub-panel are for test that coefficients of additional covariates relative to the model in column 1 are jointly equal to zero. P-values reported in column 4 of each sub-panel are for test that coefficients of additional covariates relative to model in column 3 are jointly equal to zero.

Table 4: Regression Discontinuity Estimates of Changes in Treatment Intensity

	Length of Stay				Procedure Count				Log Charges			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Age Over 65	0.37	0.36	0.35	0.39	0.09	0.10	0.11	0.13	0.024	0.026	0.026	0.036
	[0.24]	[0.26]	[0.26]	[0.35]	[0.03]	[0.03]	[0.03]	[0.04]	[0.011]	[0.011]	[0.010]	[0.013]
Year/Month/Sat/Sun	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Race and Gender	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Dummy Just Under 65	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Condition FE	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Cubic Polynomial	N	N	N	Y	N	N	N	Y	N	N	N	Y
Mean Age 64-65	8.12	8.12	8.12	8.12	2.50	2.50	2.50	2.50	9.757	9.757	9.757	9.757
Observations	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386	352,652	352,652	352,652	352,652
P-Value		0.000		0.266		0.000		0.558		0.000		0.537

Notes: See notes to Table 3. Standard errors in square brackets.

Table 5: Changes in the use of Specific Procedures for the Two Most Common Causes of Admission in the Non-deferrable Sample

Principle Diagnosis: Acute Myocardial Infarction

	Number of Procedures	No Procedures	Procedure 88.56	Procedure 37.22	Procedure 88.53	Procedure 36.01	Procedure 88.72	Procedure 99.29	Procedure 36.06	Procedure 89.54	Procedure 39.61	Procedure 37.23
Age Over 65	0.44	-1.89	3.79	3.41	4.04	0.67	2.15	1.52	0.72	2.59	1.82	0.11
	[0.12]	[0.82]	[1.54]	[1.56]	[1.57]	[1.43]	[1.41]	[1.19]	[1.08]	[1.09]	[1.09]	[1.02]
Mean 64-65	5.00	7.90	53.76	47.78	45.46	29.08	28.01	19.07	17.58	14.11	13.22	11.74
Observations	39,170	39,170	39,170	39,170	39,170	39,170	39,170	39,170	39,170	39,170	39,170	39,170
R-squared	0.01	0.00	0.05	0.03	0.01	0.03	0.03	0.10	0.21	0.05	0.01	0.01

Principle Diagnosis: Obstructive Chronic Bronchitis with Acute Exacerbation

	Number of Procedures	No Procedures	Procedure 93.94	Procedure 89.65	Procedure 93.96	Procedure 89.54	Procedure 88.72	Procedure 96.04	Procedure 96.71	Procedure 96.72	Procedure 89.52	Procedure 38.93
Age Over 65	0.00	2.01	-2.22	-0.07	-1.20	0.91	0.18	-0.04	-0.20	0.46	-0.60	-0.12
	[0.05]	[1.26]	[0.89]	[0.85]	[0.69]	[0.66]	[0.65]	[0.61]	[0.48]	[0.43]	[0.46]	[0.35]
Mean 64-65	1.19	55.38	14.66	13.56	8.13	7.00	6.80	6.18	3.80	2.68	3.34	1.89
Observations	60,514	60,514	60,514	60,514	60,514	60,514	60,514	60,514	60,514	60,514	60,514	60,514
R-squared	0.02	0.04	0.03	0.10	0.03	0.03	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors in square brackets. All models include a quadratic polynomial in age, fully interacted with a dummy for age over 65. Dummy for just under 65 is set to 1 for people admitted to the hospital in the 31 days before their 65th birthday. Race and gender represent dummies for race/ethnicity and gender. Table reports coefficient estimates from linear probability models for total number of procedures (column 1), event of no procedures (column 2) and indicators for specific procedures (columns 3-12) fit to subsamples of admissions with indicated principle admission diagnoses. Coefficient estimates for event of no procedures and for individual procedures (identified by procedure codes in column headings) are multiplied by 100, as are associated means for people with 64<=age<65. The procedures in the order they appear are: 88.56 Coronary arteriography using two catheters, 37.22 Left heart cardiac catheterization, 88.53 Angiocardiography of left heart structures, 36.01 Percutaneous transluminal coronary angioplasty, 88.72 Diagnostic ultrasound of heart, 99.29 Injection or infusion of other therapeutic or prophylactic substance, 36.06 Insertion of non-drug-eluting coronary artery stent(s), 89.54 Electrographic monitoring, 39.61 Extracorporeal circulation auxiliary to open heart surgery, 37.23 Combined right and left heart cardiac catheterization, 93.94 Respiratory medication administered by nebulizer, 89.65 Measurement of systemic arterial blood gases, 93.96 Other oxygen enrichment, 89.54 Electrographic monitoring, 88.72 Diagnostic ultrasound of heart, 96.04 Insertion of endotracheal tube, 96.71 Continuous mechanical ventilation for less than 96 consecutive hours, 96.72 Continuous mechanical ventilation for 96 consecutive hours or more, 89.52 Electrocardiogram, 38.93 Venous catheterization, not elsewhere classified.

Table 6: Regression Discontinuity Estimates of Changes in Transfer and Readmission Probabilities

	Across Hospitals				Within Hospital			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Age Over 65 (x100)	0.35	0.40	0.48	0.86	0.91	0.97	0.93	0.94
	[0.24]	[0.25]	[0.24]	[0.33]	[0.20]	[0.20]	[0.20]	[0.27]
Year/Month/Sat/Sun	N	Y	Y	Y	N	Y	Y	Y
Race and Gender	N	Y	Y	Y	N	Y	Y	Y
Dummy Just Under 65	N	Y	Y	Y	N	Y	Y	Y
Condition FE	N	N	Y	Y	N	N	Y	Y
Cubic Polynomial	N	N	N	Y	N	N	N	Y
Mean Age 64-65 (x100)	6.87	6.87	6.87	6.87	4.02	4.02	4.02	4.02
Observations	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386
P-Value		0.000		0.236		0.000		0.436
	Readmission Within 7 Days of Discharge				Readmission Within 28 Days of Discharge			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Age Over 65 (x100)	-0.36	-0.18	-0.16	-0.48	-0.92	-0.61	-0.63	-0.79
	[0.24]	[0.24]	[0.24]	[0.34]	[0.36]	[0.37]	[0.37]	[0.50]
Year/Month/Sat/Sun	N	Y	Y	Y	N	Y	Y	Y
Race and Gender	N	Y	Y	Y	N	Y	Y	Y
Dummy Just Under 65	N	Y	Y	Y	N	Y	Y	Y
Condition FE	N	N	Y	Y	N	N	Y	Y
Cubic Polynomial	N	N	N	Y	N	N	N	Y
Mean Age 64-65 (x100)	6.59	6.59	6.59	6.59	17.02	17.02	17.02	17.02
Observations	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386
P-Value		0.000		0.310		0.000		0.800

Notes: See notes to Table 3. Standard errors in square brackets. Admissions with missing Social Security Numbers cannot be tracked and are dropped from the sample used in this table

Table 7: Regression Discontinuity Estimates of Changes in Mortality Rates

	Died Within 7 Days of Admission				Died Within 14 Days of Admission				Died Within 28 Days of Admission			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Age Over 65 (x100)	-1.1	-1.1	-1.0	-0.7	-1.0	-1.0	-0.8	-0.7	-1.1	-1.0	-0.9	-0.6
	[0.2]	[0.2]	[0.2]	[0.3]	[0.2]	[0.2]	[0.2]	[0.3]	[0.3]	[0.3]	[0.3]	[0.4]
Year/Month/Sat/Sun	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Race and Gender	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Dummy Just Under 65	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Condition FE	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Cubic Polynomial	N	N	N	Y	N	N	N	Y	N	N	N	Y
Mean Age 64-65 (x 100)	5.1	5.1	5.1	5.1	7.1	7.1	7.1	7.1	9.8	9.8	9.8	9.8
Observations	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386
P-Value		0.000		0.311		0.000		0.860		0.000		0.598

	Died Within 90 Days of Admission				Died Within 180 Days of Admission				Died Within 365 Days of Admission			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Age Over 65 (x100)	-1.1	-1.0	-0.9	-0.9	-1.2	-1.1	-0.8	-0.9	-1.0	-0.9	-0.7	-0.4
	[0.3]	[0.3]	[0.3]	[0.4]	[0.4]	[0.4]	[0.3]	[0.5]	[0.4]	[0.4]	[0.4]	[0.5]
Year/Month/Sat/Sun	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Race and Gender	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Dummy Just Under 65	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y
Condition FE	N	N	Y	Y	N	N	Y	Y	N	N	Y	Y
Cubic Polynomial	N	N	N	Y	N	N	N	Y	N	N	N	Y
Mean Age 64-65 (x 100)	14.7	14.7	14.7	14.7	18.4	18.4	18.4	18.4	23.0	23.0	23.0	23.0
Observations	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386	407,386
P-Value		0.000		0.466		0.000		0.154		0.000		0.104

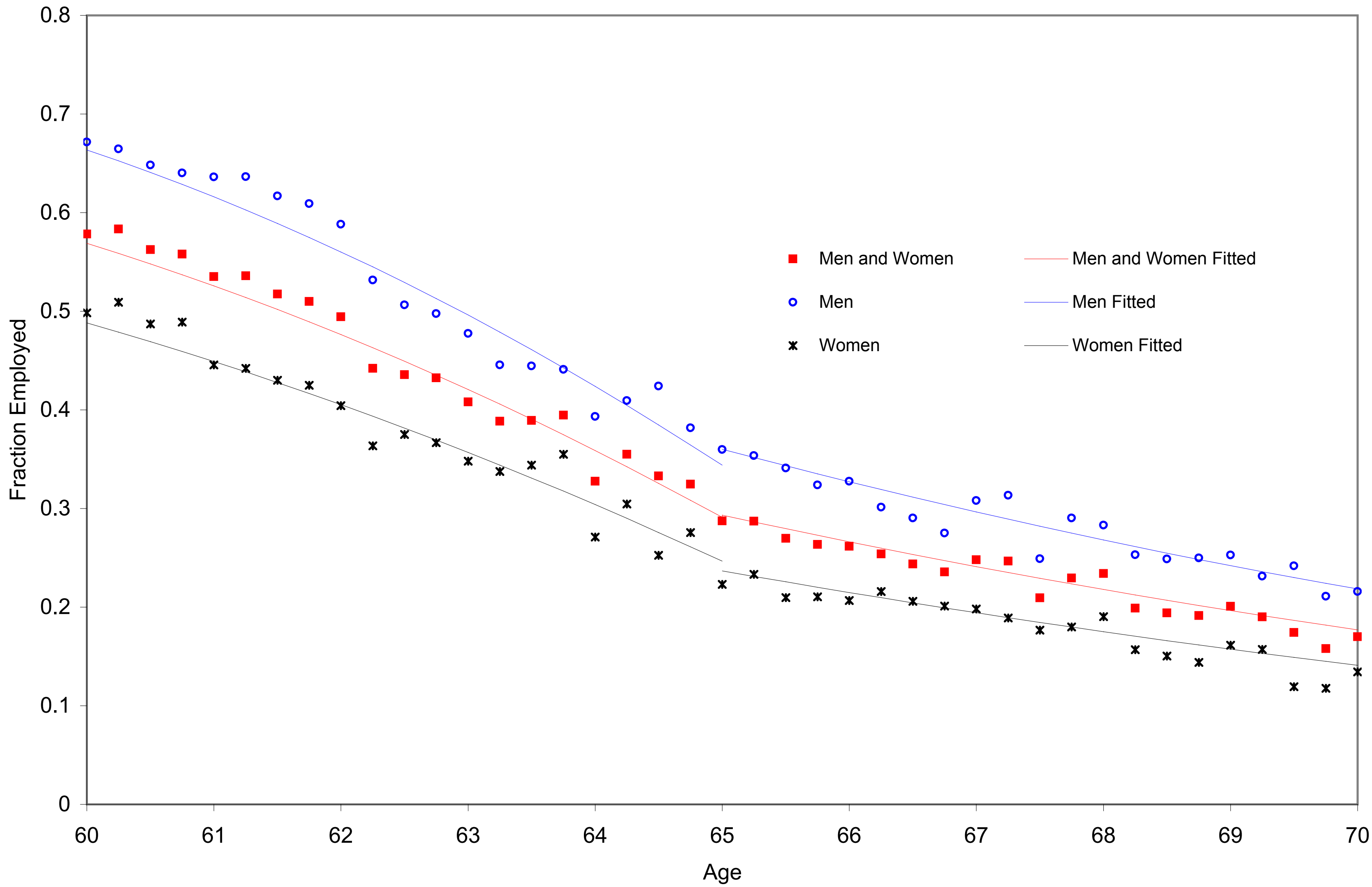
Notes: See notes to Table 3. Standard errors in square brackets. Admissions with missing Social Security Numbers cannot be linked to death records and are dropped from the sample used in this table

Table 8: Lower Bound Estimates of Effect of Medicare Eligibility on 28-day Mortality for Various Samples

	All	Elective	ER and Unplanned	ER and Unplanned (> 6.62)	(2.54-6.51)	(0.96-2.54)	(< 0.96)
1. RD in Admissions %	7.12	11.85	2.43	3.23	3.57	2.70	0.56
2. RD in Mortality	-0.46	-0.29	-0.49	0.27	-0.63	-0.45	-1.09
3. Just Under 65 death rate	5.10	3.29	6.86	2.68	7.41	6.87	10.25
4. Worst Case Bias	-0.33	-0.36	-0.15	-0.10	-0.24	-0.17	-0.05
5. Lower Bound Estimate	-0.13	0.06	-0.33	0.37	-0.39	-0.27	-1.04
6. SE on Lower Bound	0.07	0.09	0.12	0.16	0.25	0.24	0.29
7. Share of Obs	1.00	0.50	0.50	0.11	0.13	0.12	0.12

Notes: See text for discussion of lower bound formula. All terms are expressed as percentages. Entry in row 1 is estimated regression discontinuity (RD) in log admissions at age 65 (multiplied by 100). Entry in row 2 is estimated RD in 28-day mortality at age 65 (in percents). Entry in row 3 is estimated 28-day mortality rate for people just under 65 (in percents). Entry in row 4 is estimated worst-case bias in 28 day mortality caused by selective increase in admissions rates after age 65 (in percents). Entry in row 5 is lower bound estimate of effect of Medicare eligibility on 28-day mortality rate (in percents). Entry in row 6 is estimated standard error of lower-bound mortality effect (in percents) estimated by delta method. Entry in row 7 is share of total sample included in column sub-sample. Sub-samples in columns 4-8 do not add up to overall sub-sample of ER and unplanned admissions in column 3 because admissions whose primary diagnosis accounts for less than 100 observations in the overall sample have been dropped.

Appendix A: Employment Rates by Age (1992-2003 NHIS)

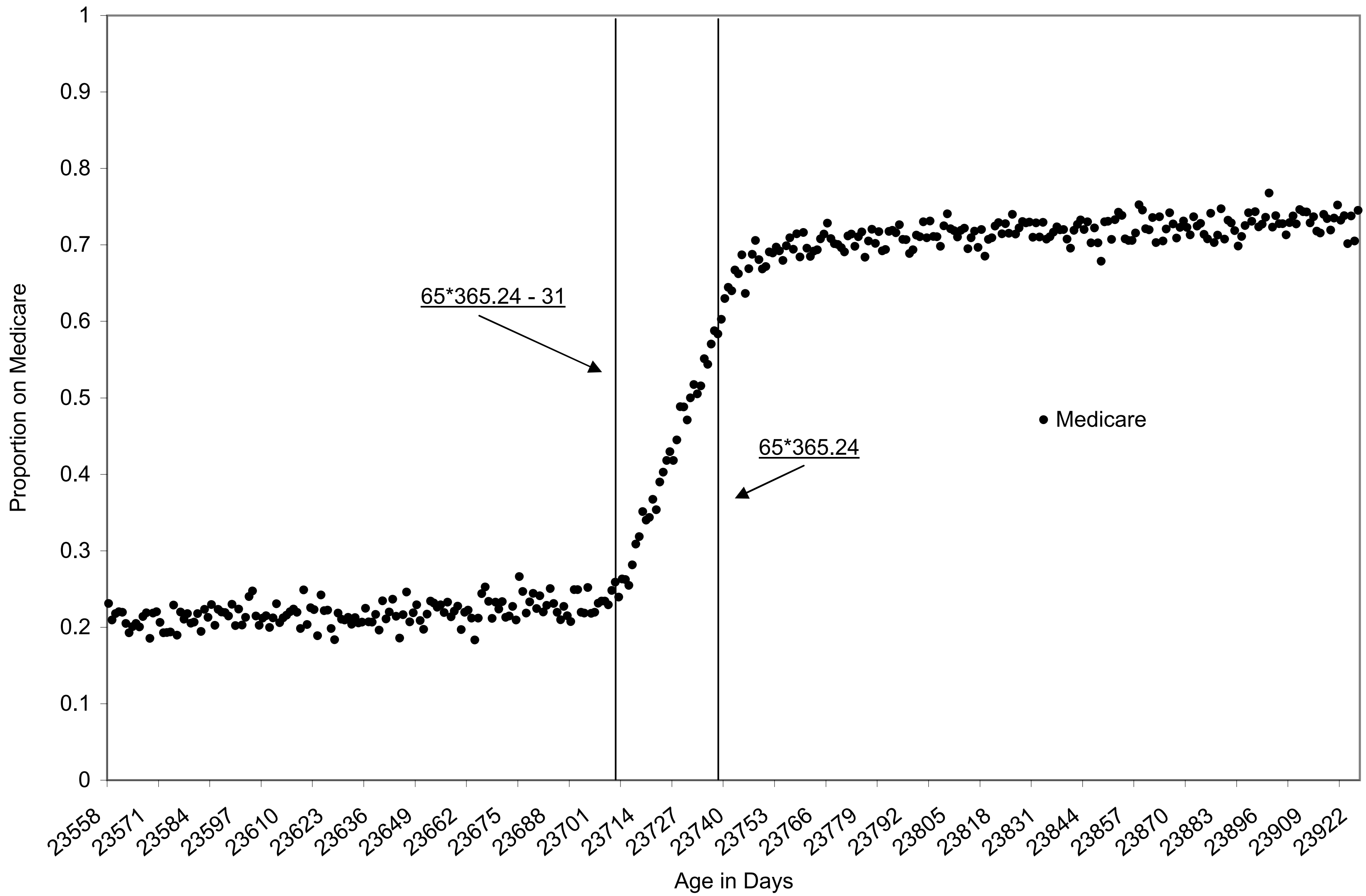


Appendix B: RDD in Admissions Estimated With a Cubic Polynomial

	Non ER or Planned		ER and Unplanned		Weekend t-stat > 6.62	
Age Over 65	0.12028	0.13144	0.02568	0.03825	0.0332	0.0564
	[0.00493]	[0.00693]	[0.00498]	[0.00692]	[0.01069]	[0.01465]
Dummy Age 64.91-65	Y	Y	Y	Y	Y	Y
Cubic Polynomial	N	Y	N	Y	N	Y
Observations	3,652	3,652	3,652	3,652	3,652	3,652
R-Squared	0.87	0.87	0.81	0.81	0.39	0.39
	Weekend t-stat 2.54-6.62		**Weekend t-stat 0.96-2.54**		**Weekend t-stat < 0.96**	
Age Over 65	0.0369	0.04436	0.03045	0.04183	0.00608	0.01932
	[0.00974]	[0.01357]	[0.00982]	[0.01378]	[0.00924]	[0.01270]
Dummy Age 64.91-65	Y	Y	Y	Y	Y	Y
Cubic Polynomial	N	Y	N	Y	N	Y
Observations	3,652	3,652	3,652	3,652	3,652	3,652
R-Squared	0.54	0.54	0.63	0.63	0.52	0.52

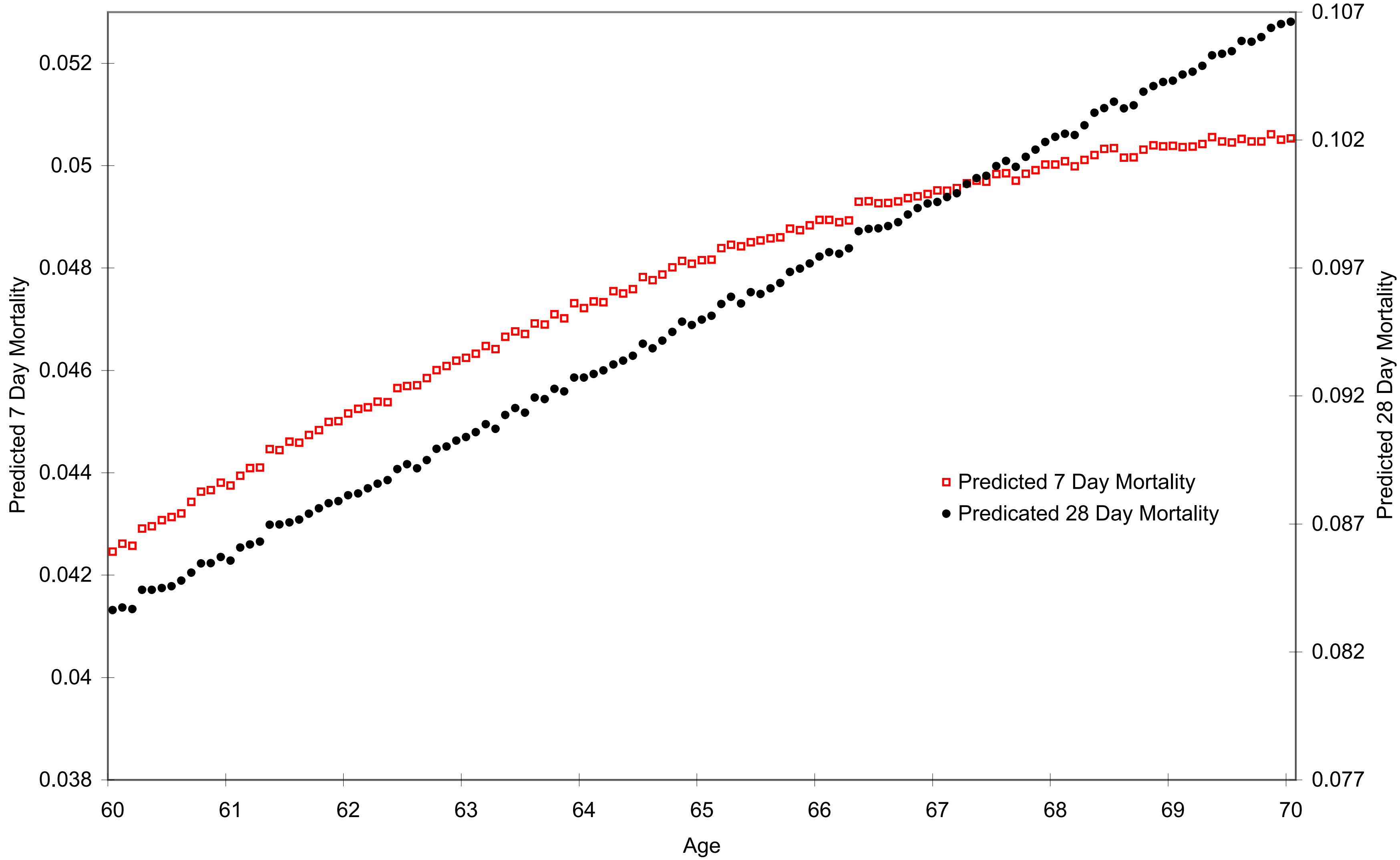
Notes: See notes from Table 2.

Appendix C: Proportion on Medicare by Age in Days



Note: People become eligible for Medicare on the 1st day of the month in which they turn 65. The youngest age at which a person can be eligible is 365.24*65 - 30. Everyone is eligible after their 65th birthday 65*365.24.

Appendix D: Predicted Mortality Probabilities



Notes: Mortality predicted from a quadratic in age, condition FE, gender, race, ethnicity, year, month and day of week of arrival to the hospital.