Does Medicare Save Lives?

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Abstract

The health insurance coverage of the population changes sharply at age 65 as most people become eligible for Medicare. But do these changes matter for health? We answer 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 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 coverage of the two groups is 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 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, overall admission rates 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 coverage we find a 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 (26%) increase in the likelihood that patients are transferred to other units within the same hospital, most commonly skilled nursing facilities. 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 7 days of admission. Given a 7-day mortality rate of about 5 percent in our sample of severely ill patients, this represents a 20 percent reduction in mortality. This gap 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 to be driven entirely by this group. Moreover, we find only slightly larger changes in treatment intensity and mortality for patients from zip codes with relatively low rates of insurance coverage pre-65 (who experience a 10-point gain in coverage at 65) than for patients from high-coverage zip codes (who experience a much smaller gain). 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.

In the next section we present 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 available to people who are 65 or older and have worked at least 10 years in covered employment.[1] Coverage is also provided to recipients of Social Security Disability Insurance (DI): currently about 12% of the population is already on Medicare 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 this fact using four different dimensions of insurance coverage: the probability of Medicare coverage; the probability of any coverage; the probability of coverage by multiple insurance policies; and the probability that an individual's primary insurance coverage is a managed care policy. The data for this analysis are drawn from the 1999-2003 National

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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

Health Interview Survey (NHIS). The figure shows the means of each characteristic by age (measured in quarters), as well as the predicted 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 NHIS data show a jump of about 60 percentage points in the fraction of people with Medicare coverage at age 65.[3] Apart from this jump the age profile is relatively smooth and well-described by a simple quadratic function. Associated with the rise in Medicare enrollment 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 (versus about 13% of those under 65).

The other characteristics plotted in Figure 1 also show big changes at age 65. The fraction of the population covered by multiple insurance policies rises by about 45% as many people holding private coverage before their 65th birthday enroll in Medicare *and* a supplemental insurance policy once they reach 65.[4] Conversely, the fraction of people whose primary health insurance is a managed care policy drops by about 30%. This drop reflects the relatively high rate of managed care coverage in the private insurance market, contrasted with the 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,

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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.

[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. Medicare HMO plans offer more complete coverage (including drug benefits, prior to the introduction of Part D in 2006) but are relatively unpopular.

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 multiple-coverage. And, since most Medicare recipients choose traditional fee-for-service coverage, the fraction of the population with managed care also drops.

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.

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[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.

As is true for health insurance more generally (Levy and Meltzer, 2004), it has proven more difficult to identify the health impacts of Medicare. Most existing studies have focused on mortality as an indicator of health.[6] Lichtenberg (2001) uses Social Security Administration (SSA) life tables to test for a trend-break in the age profile of mortality at age 65. Although he identifies a break, subsequent analysis by Dow (2004) shows that this is an artifact of the interval smoothing procedure used to construct the SSA life tables. Comparisons based on unsmoothed data (e.g., Card, Dobkin, Maestas, 2004) show no evidence of a shift at age 65. 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 provides any evidence 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 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 mortality. By comparison, Medicare-

[6] 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.

induced services would have to have a very large impact on mortality to generate a detectable effect on a relatively healthy population.[7]

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 function), $Post65_i$ 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 re-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.[8] 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

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[7] 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 "problem" is that the baseline mortality rate of 65 year olds is only about 1.5% per year.

[8] 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.

switching from an insurance carrier other than Medicare to a package that includes Medicare;[9] (3) an effect attributable to the change from managed care coverage to indemnity insurance. Any or all of these channels could result in an increase in health services once people reach 65, with a potential effect on health.

As emphasized by Lee (2007), the key assumption underlying an RD analysis such as equation (1) 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. This implies 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 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 over 65 status is unlikely to hold 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 potential difficulty, using counts of hospital admissions based on California discharge records from 1992 to 2002. (The sample is described more precisely below). The age profile of admissions is very smooth, apart from a jump at precisely 65. The number of non-Emergency Room admissions jumps by 12% at 65, while the number of Emergency Room admissions rises by 3%. This jump suggests that the population of patients who are just over 65 is healthier than the population just under 65, since the over-65 group includes people who

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[9] Arguably, one could break out this effect into an effect associated with Medicare coverage per se, and an effect

elected to enter given they were Medicare-eligible, but would not have done so if they were slightly younger.

In this paper we resolve 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 the same ER admission rate on weekdays and weekends.[10] 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 exercise (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.

associated with coverage by multiple policies.

Even if there is no differential selection around the discontinuity threshold, inferences from an RD design can be compromised if there are multiple factors that change at the threshold. One concern here is retirement. Sixty-five is a traditional retirement age, and studies have shown that health is affected by employment status (Ruhm, 2000). We believe this concern is relatively minor. First, as discussed in more detail in the Appendix, recent data show no discontinuity in the likelihood of working at exactly age 65.[11] 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 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.

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. Patients must have been admitted to the hospital; thus, those who were sent home after treatment in the

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[10] 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.

[11] 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.

emergency room do not appear in the sample.[12] As explained in the Appendix, 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 the 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 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, and this rate drops by about 1 percentage point at age 65. Because the in-hospital mortality rate of those missing an SSN is much higher than that of those with an SSN (10.4% v. 6.3%), the addition of patients with systematically higher mortality after 65 would tend to bias down any observed mortality improvements at 65. In any case, in Section V.b., 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.

[12] 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.

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 admissions 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 very few ICD-9 codes with 2/7 of all admissions entering on the weekend. 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 diagnosis codes 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.

Table 1 summarizes the 10 most common admission diagnoses codes in this subsample of 424,694 "non-deferrable" admissions. The largest diagnosis category is obstructive chronic bronchitis with acute exacerbation (these complications include emphysema, asthma, and heart disease). Patients with these conditions have an average hospital stay of 6.25 days, an average of 1.21 procedures performed during their stay, and a 3% in-hospital death rate. Most of the other relatively common admission codes result in even longer stays, more procedures, and a higher rate of in-hospital death. Evidently, admission diagnoses with a similar 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 8 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, and the discussion in the Appendix).

A limitation of our data is that although we know age in days, we do not know a patient's date of birth or exact admission date.[13] 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. This fraction is relatively flat for people in the year prior to the 31 days before their 65th birthday, and in the year after, but rises linearly in the intervening period, as would be expected given the eligibility rules assuming 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. This addition has relatively little impact on the estimated coefficient for the post-65 dummy, though in cases when the Post65 effect is significantly positive in the first specification, the second specification shows a slightly larger effect at 65 (consistent with the idea that the observations just to the left of the 65 threshold are "partially treated"). Looking at the first two panels, we estimate that non-ER or planned 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 on the test for a constant weekday/weekend admission rate.

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 of the test to detect differences in patient

[13] This restriction was imposed by the California Department of Health and Human Services as a condition for

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 a 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 patients in the non-deferrable subsample who are just under and just over 65 are equally healthy.

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

a. Insurance and Treatment Intensity

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) in the non-deferrable admissions subsample. As expected given the results in Figure 1, 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 these various outcomes are presented in Table 3. This table has the same format as Table 2, although we now include a set of

access to the discharge files.

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.

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.[14] Note that in the sample of non-deferrable admissions the Medicare coverage rate at age 64 is about 21%, somewhat higher than in the overall population. 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.

Next, we turn to measures of the intensity of treatment in the hospital. We have three basic measures of intensity: length of stay, number of procedures performed, and hospital list charges.[15] 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

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[14] 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.

[15] 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 people in HMO's. However, the sum of list charges for a patient is a convenient "weighted summary" of services used in the hospital.

estimation results in Table 4 show that mean length of stay increases by 0.4 days (or about 4.5%) at 65, though the 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 provide further confirmation 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).

Another indicator of treatment intensity is the probability that a patient is transferred to another care/treatment unit in the same hospital, or to second hospital.[16] Depending on the nature of the transfer, this outcome could be interpreted as another measure of treatment intensity, as an indirect measure of treatment success during the initial hospital stay. Figure 7 shows the age profiles of transfer outcomes. Both within- and between-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 5, and confirm that the within-hospital transfer rate rises by about 1 percentage point (on a base level of about 3.7% among 64 year olds) once patients are over 65.

Further analyses (not shown) indicate that the additional within-hospital transfers are primarily transfers to skilled nursing facilities. The jump in transfers to skilled nursing facilities once patients become Medicare-eligible provides an interesting example of hospitals' responsiveness to Medicare reimbursement policies. 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. Newhouse (2002) argues that the differential reimbursement schemes led to dramatic growth in skilled nursing facilities (both within hospitals and in free-standing units), accompanied by a shift in care from acute to post-acute settings. The rise in transfers to these facilities at age 65 is consistent with this argument.

Finally, Figure 8 and the RD models in the lower panel of Table 5 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 "success" of treatment in the initial hospital stay, although this interpretation is clouded by any 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 slightly. The RD models suggest that the 28-day readmission rate is about ½ of one percent lower for people just over 65, though the sampling error is relatively large, yielding a t-ratio of only about 1.6 or less.

b. 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 6 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 6 confirm this: we observe a reduction in 7-day mortality of about 1

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[16] When a patient is transferred, he or she is discharged and then admitted to the new unit. We have collapsed all

percentage point which persists (or fades only slightly) 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.[17] 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 provided to Medicare-eligible admittees during their hospital stay have an immediate life-saving effect, and that treatments lead to a substantial gain in the duration of life.

In light of the more modestly-sized changes in number of procedures performed and in list charges, the estimated mortality effect does <u>not</u> appear to be driven by the performance of additional high-cost, invasive procedures. This interpretation is consistent with a large literature that has analyzed the effect of invasive procedures such as bypass and angioplasty on the subsequent mortality of patients with acute myocardial infarction (AMI), and has concluded that such procedures have at most a small impact on mortality rates (e.g., McClellan, McNeil and Newhouse, 1994; Cutler, McClellan, Newhouse, 1999). In fact, AMI patients constitute only

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consecutive hospital stays to a single record, dated at the initial admission, to avoid double counting.

[17] These estimates are from our base specification with no additional controls (i.e., the first specification in each panel of Table 6).

about one-quarter of our sample. The largest admissions categories involve breathing problems, most commonly related to chronic obstructive pulmonary disease, for which standard practice does not typically involve high-cost, invasive procedures (this can be seen in Table 2). While our data do not permit further inference about the nature of the extra life-saving services rendered to Medicare patients, these could include pre-hospital emergency services, diagnostics, monitoring, and services provided during post-acute care. Given that the mortality differentials arise rapidly within 7 days of admission, we believe the latter to be less likely.

It is also worth underscoring that our results point to differential treatment of Medicare patients within hospitals, rather than patient sorting to higher-quality hospitals at 65. Although we do observe a 3% reduction in non-deferrable admissions to county hospitals at age 65, the pre-65 mortality rate associated with county hospitals would have to be substantially larger than that of private hospitals for sorting to be an explanation for our results. In our sample, however, 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%), and district hospitals (9.7%).[18] In other words, it does not appear that Medicare eligibility buys access to better hospitals, but rather it may buy better care within a given hospital.

To probe the credibility of these estimated 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 potentially two subgroups: a first group (which we index with subscript 1) who enter the hospital

[18] 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.

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 will contain 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:

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

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:

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

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

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

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

Table 7 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 (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. Row 1 shows estimates of the fraction α for each patient group, based on the jump in the log of the number of hospital admissions at age 65. Rows 2-4 show the estimated mortality rates of patients just under and just over 65, and the change in mortality at 65 (obtained from a quadratic RD specification similar to the one used in the second column of each panel of Table 6). Row 5 shows our estimate of the worst-case selectivity bias, based on equation (4), while row 6 shows our lower bound estimate of the effect of Medicare eligibility on the patient population. Finally, for reference row 7 shows the fraction of patients in each subgroup.

Several 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 -0.14%. 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 essentially 0. This is also true for ER admissions in the top quartile of weekend/weekday admission codes. For these two groups 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 Medicare mortality effect for the unplanned ER group in column 4 with the lowest relative admission rate on weekends (and therefore the highest t-ratio) is actually slightly positive (+0.31%). 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.[19] Second, the diagnoses in this quartile are relatively benign. In particular, the 28-day mortality rate for 64- year-old patients in this group is only 2.6%, 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, and a negative effect on patient mortality, particularly for acutely ill patients with non-deferrable diagnoses. In this section we discuss the possible channels for this effect. To aid in this discussion it is helpful to consider a simplified "triangular" 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:

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

$$(5) \qquad z_i = g(a_i, \gamma_z) + \text{Post65}_i\, \pi + \upsilon_{zi} ,$$

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:[20]

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

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 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.

[20] 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).

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 <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.

We can gain some added insight by comparing changes in health insurance, the intensity of treatment, and mortality for different subgroups of patients. 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.[21]

We have conducted comparisons across subgroubs of our non-deferrable admission sample by race and ethnicity. Unfortunately the sample sizes for blacks (n=41,000) and Hispanics (n=66,280) are too small to obtain useful estimates. A more informative contrast is

[21] In principle, if the number of groups is bigger than the number of insurance characteristics, and the discontinuities in insurance, mortality and services are observed, then the parameters λ and θ are identifiable. These conditions are not satisfied in our context.

between patients from different zip codes. We divided zip codes into two groups by estimating the fraction of 55-64 year old patients (with nondeferrable conditions) from each zipcode who had no insurance coverage, and grouping zip codes into those with lower and higher rates of uninsurance. Estimates of our RD models for various outcomes for these two groups are presented in Table 8.

As expected, the gain in insurance coverage is much larger for patients from low-insurance zip codes (+10.7%) than for those from high-insurance zip codes (+5.3%). The net changes in primary insurer are also different, with more of the patients from low-insurance zip codes moving from Medicaid to Medicare at age 65, and more of the patients from high-insurance zip codes moving from private insurance to Medicare. The changes in measures of treatment intensity point to rises for both groups, with a 10-30% bigger gain at age 65 for patients from low-insurance zip codes. In particular the relative rise in the the mean length of stay (+0.39 versus +0.35), the number of procedures (+0.12 versus +0.09) and the rate of within-hospital transfers (+1.1% versus +0.9%) are all bigger for this group, though in no case is the differential statistically significant.[22] Interestingly, the relative change in mortality is also about 30% bigger for patients from low-insurance zip codes.

While imprecise, the pattern of the estimates in Table 8 is consistent with a roughly proportional link between relative gains in treatment intensity and relative reductions in mortality. The link to changes in specific insurance characteristics is less clear, although the relative changes in treatment intensity (and mortality) are much smaller than the relative change in uninsurance, suggesting that a pure "coverage effect" cannot be the whole explanation for the patterns across these two groups of zip codes. Instead, it seems that the onset of Medicare eligibility leads to increases in treatment intensity and reductions in mortality for people who had insurance coverage prior to 65, perhaps because Medicare imposes fewer restrictions than private insurance or Medicaid. Supporting this interpretation is our finding that within-hospital transfers to skilled nursing facilities rise by 26% at exactly age 65, indicating that hospital treatment patterns are quite sensitive to insurer reimbursement incentives. This conclusion is similar to the finding in Card, Dobkin, and Maestas (2007) where we note that Medicare eligibility leads to increases in hospitalization rates for a wide range of procedures, and that the increases are generally bigger for whites than blacks or Hispanics, even though whites tend to have higher rates of insurance coverage (particularly private insurance) 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 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.

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[22] Note that the jump in list charges at age 65 is actually bigger for patients from high-insurance zip codes.

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, particularly skilled nursing facilities. 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 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 conclude that the lives saved by Medicare are widely distributed across the population. We argue that this pattern is more consistent with a generosity channel, perhaps characterized by 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.

In conclusion, we note that this large gain in mortality is achieved with only a modest rise in list charges. This suggests a very favorable benefit-cost analysis at even lower bound estimates of the value of a lifeyear saved.

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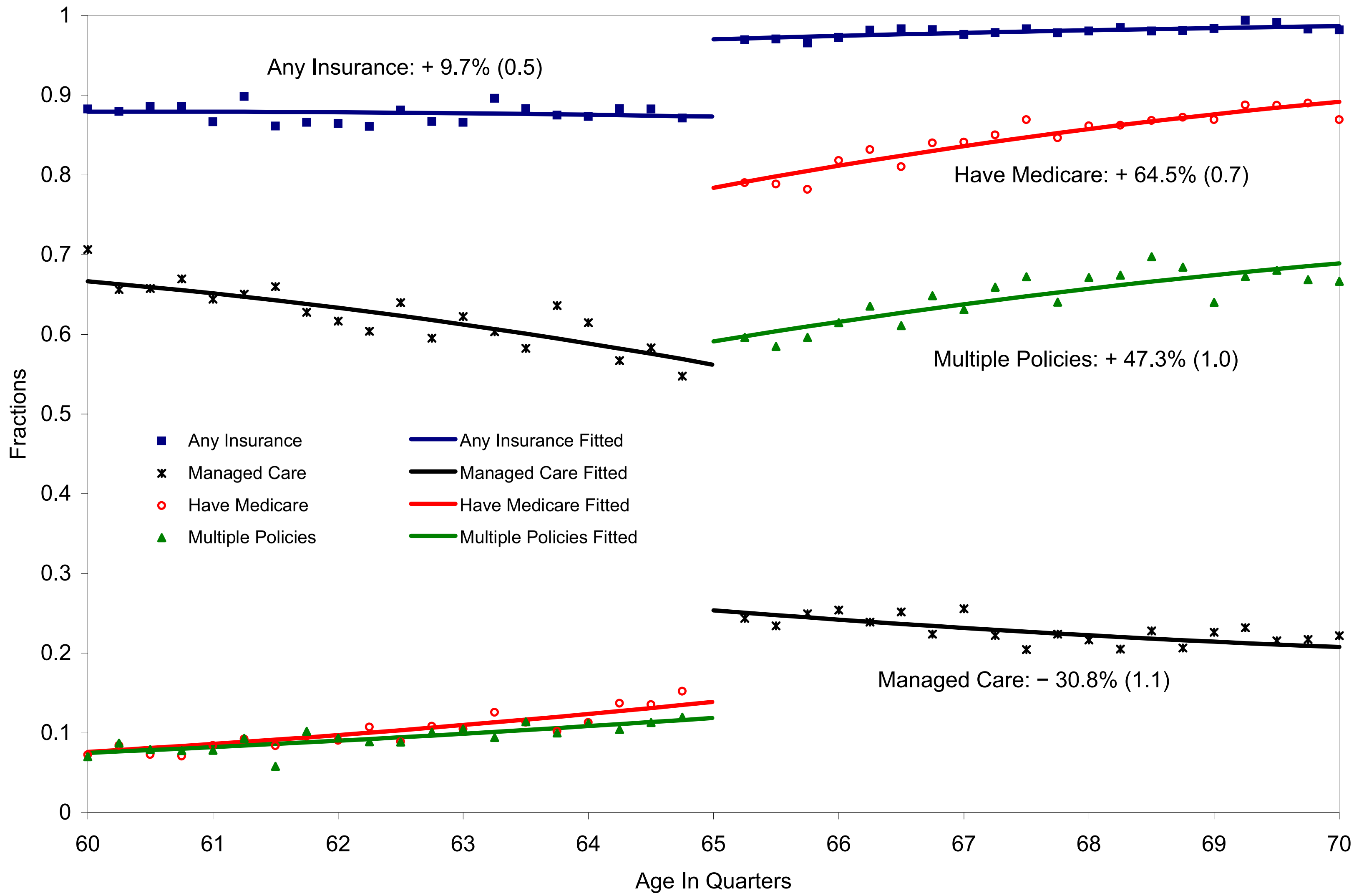
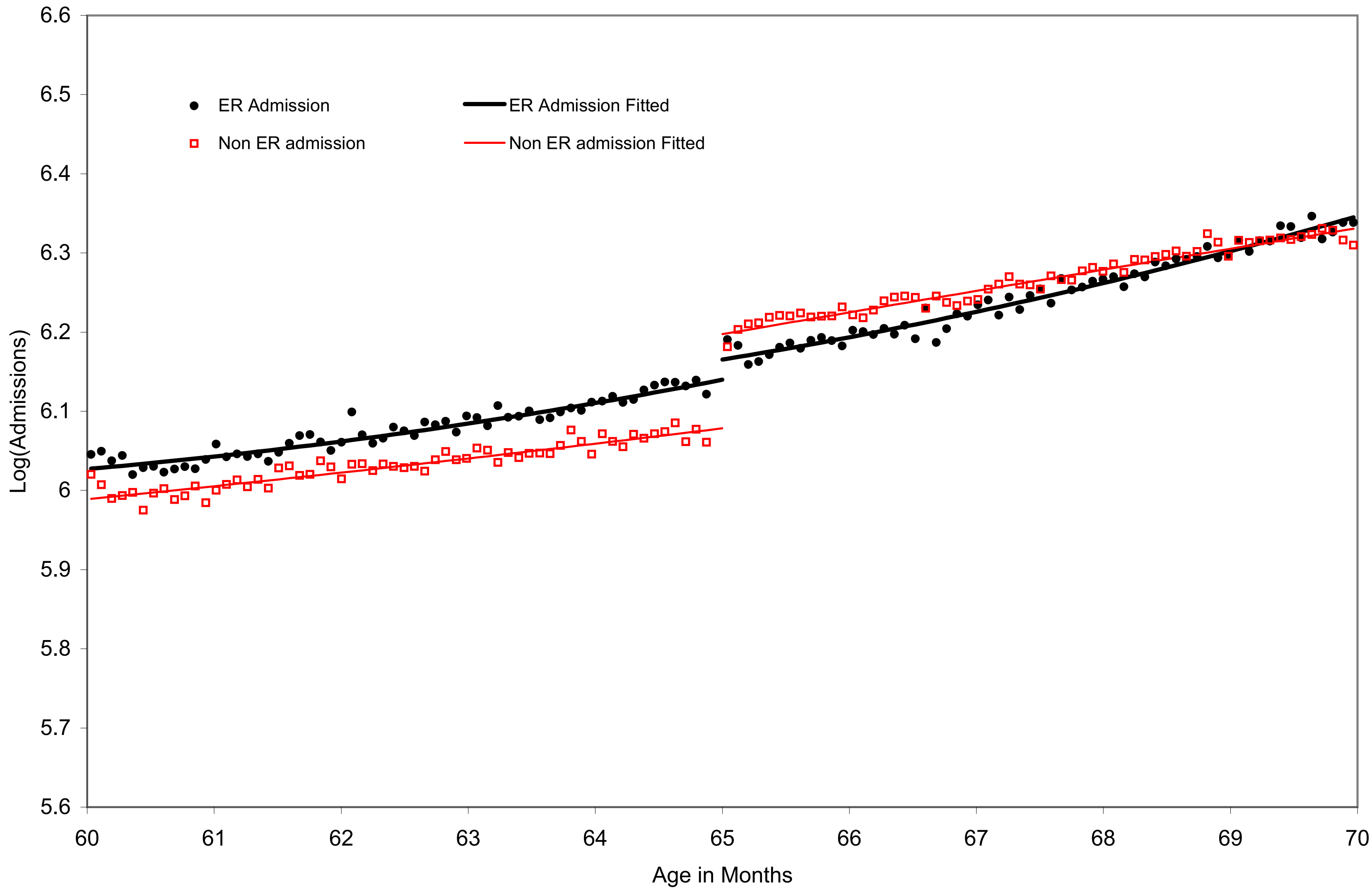
Figure 1: Changes in Health Insurance at Age 65, National Health Interview Data



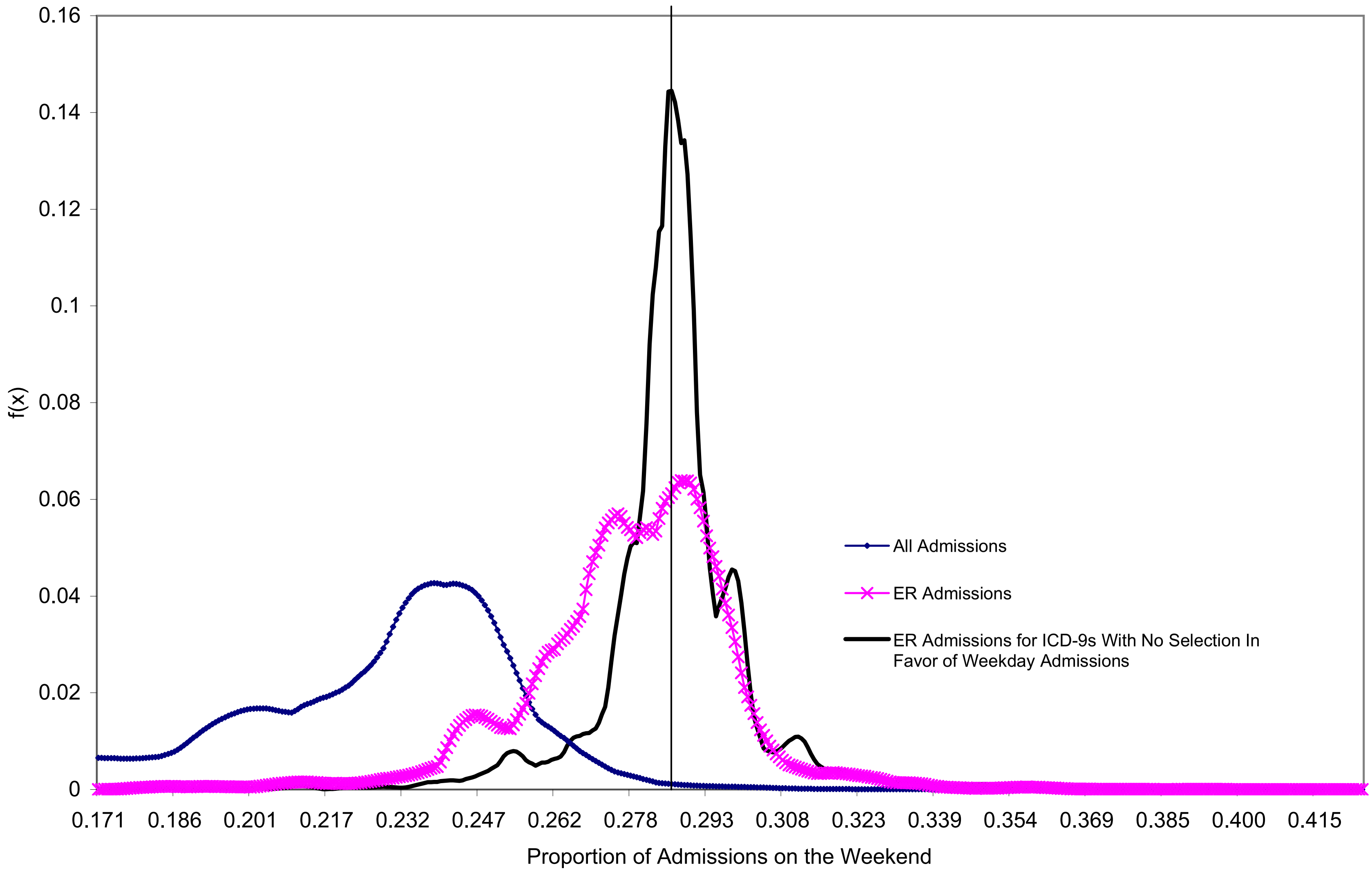
Notes: Estimated discontinuities (and standard errors) at age 65 from fully interacted quadratic shown. Models include dummy for uncertainty of eligibily status of people assigned to age=65.0. This point has been dropped fromthe figure.

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



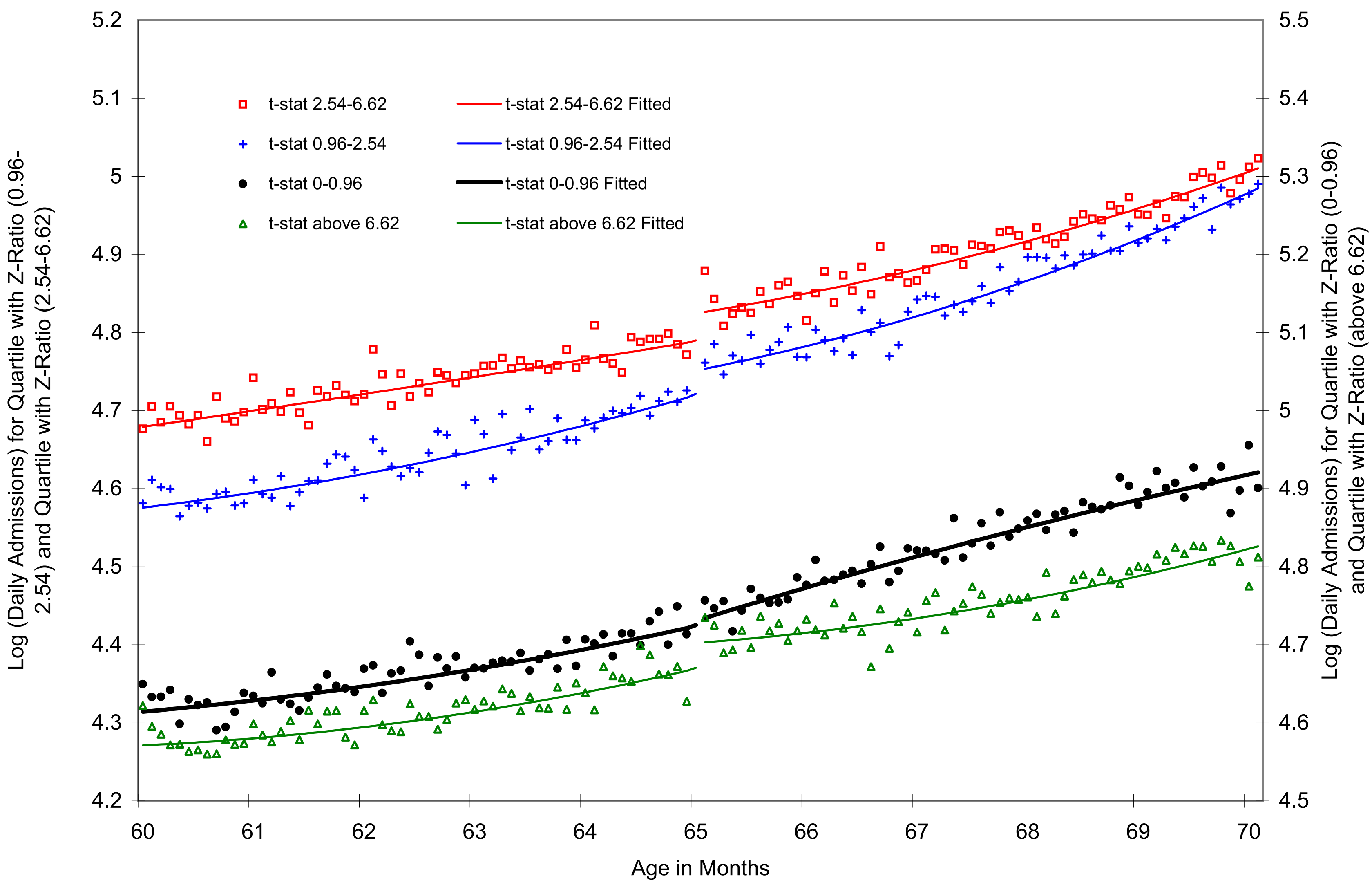
Notes: The points are the log of the average admission count. The fitted values are from regressions that include a second order polynomial in age fully interacted with a dummy for age >= 65 and a dummy variable for the month before people turn 65.

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



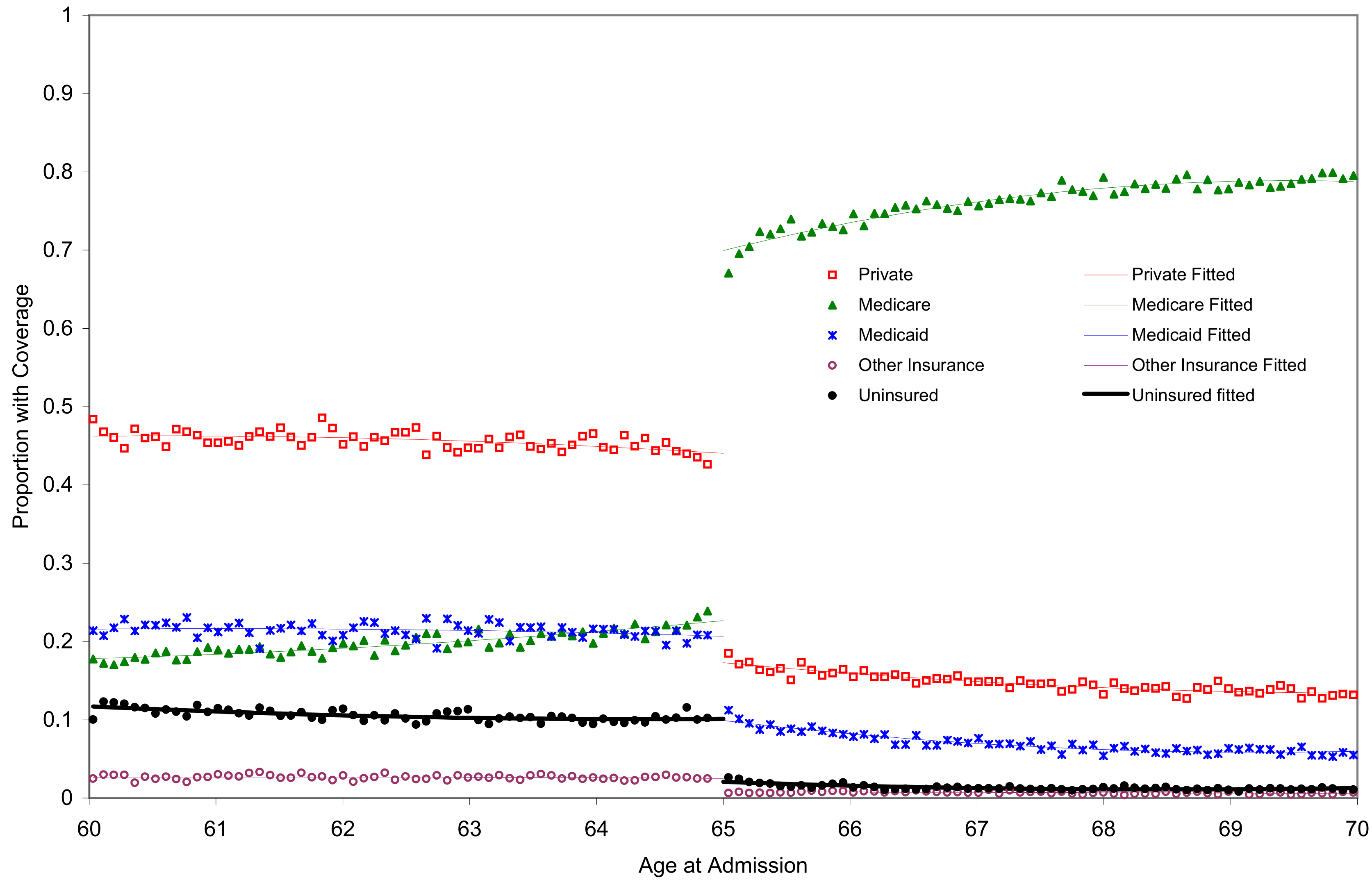
Notes: To create the figures above we computed the proportion of patients admitted on the weekend for each ICD-9. We then computed the KDE of the weekend admissions proportions over the ICD-9s. We repeated the process for admissions through the ER.

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



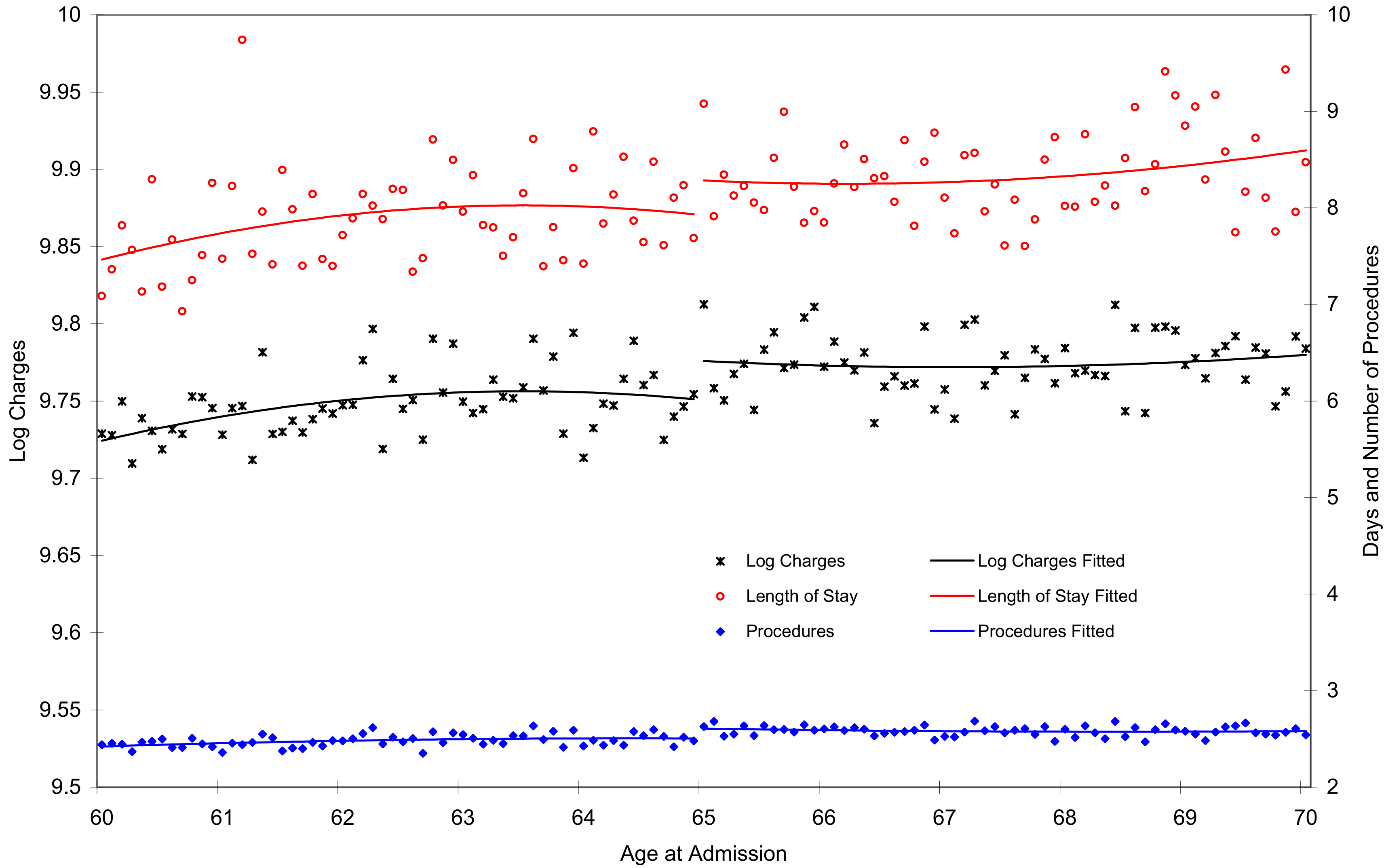
Notes: See notes from Figure 2. For the sample of ER admissions the age profiles above are created by computing the t-statistic for the test that an ICD-9 has a weekend to weekday ratio of 2:5. The admissions into quartiles based on the t-statistic.

Figure 5: Primary Insurance Coverage



Notes: Coverage is the expected primary payers. These figures are derived from the 424,694 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. Actual charges are typically substantially lower than list charges.

Figure 7: Transfer Admission to the Hospital

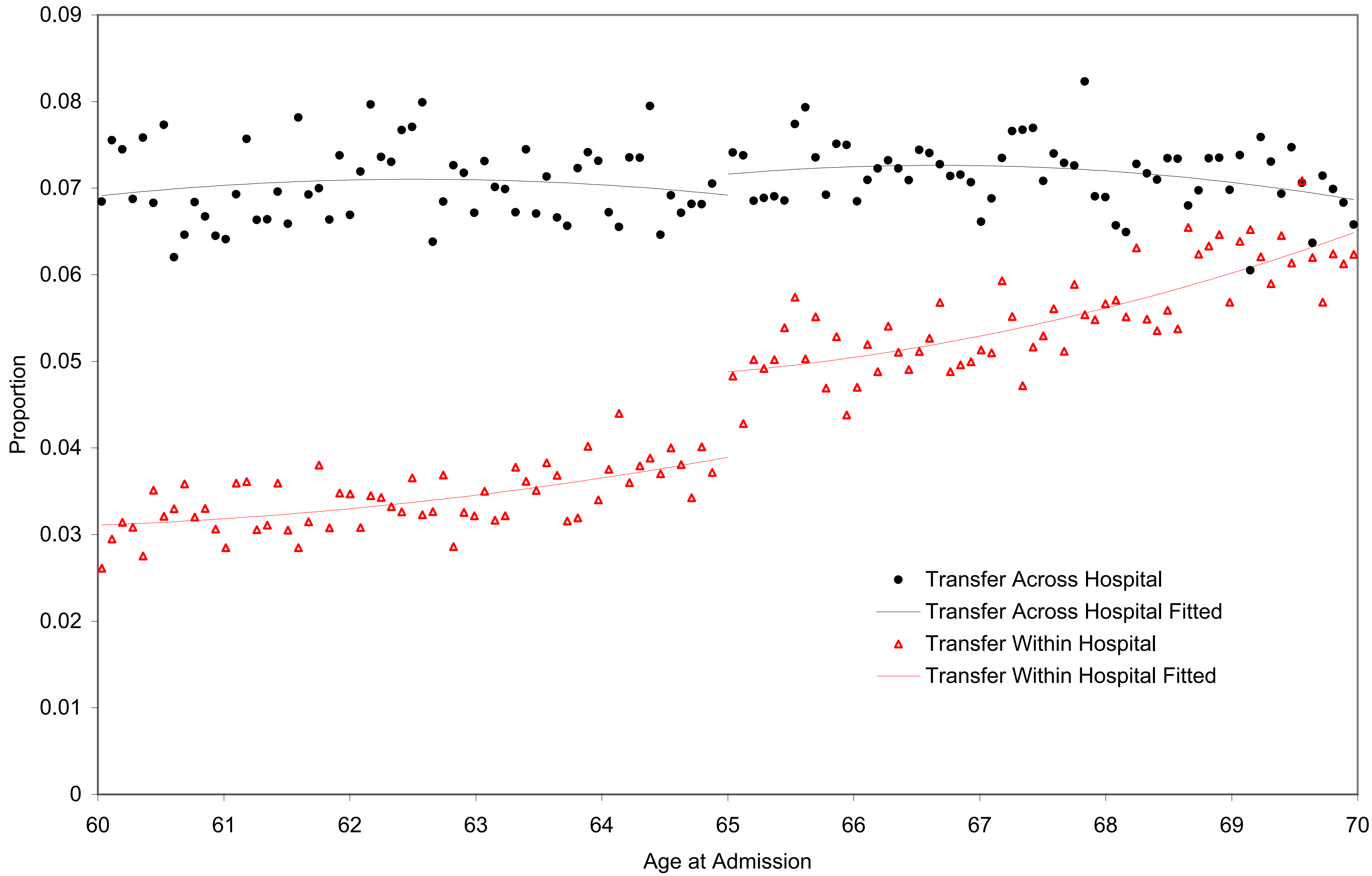
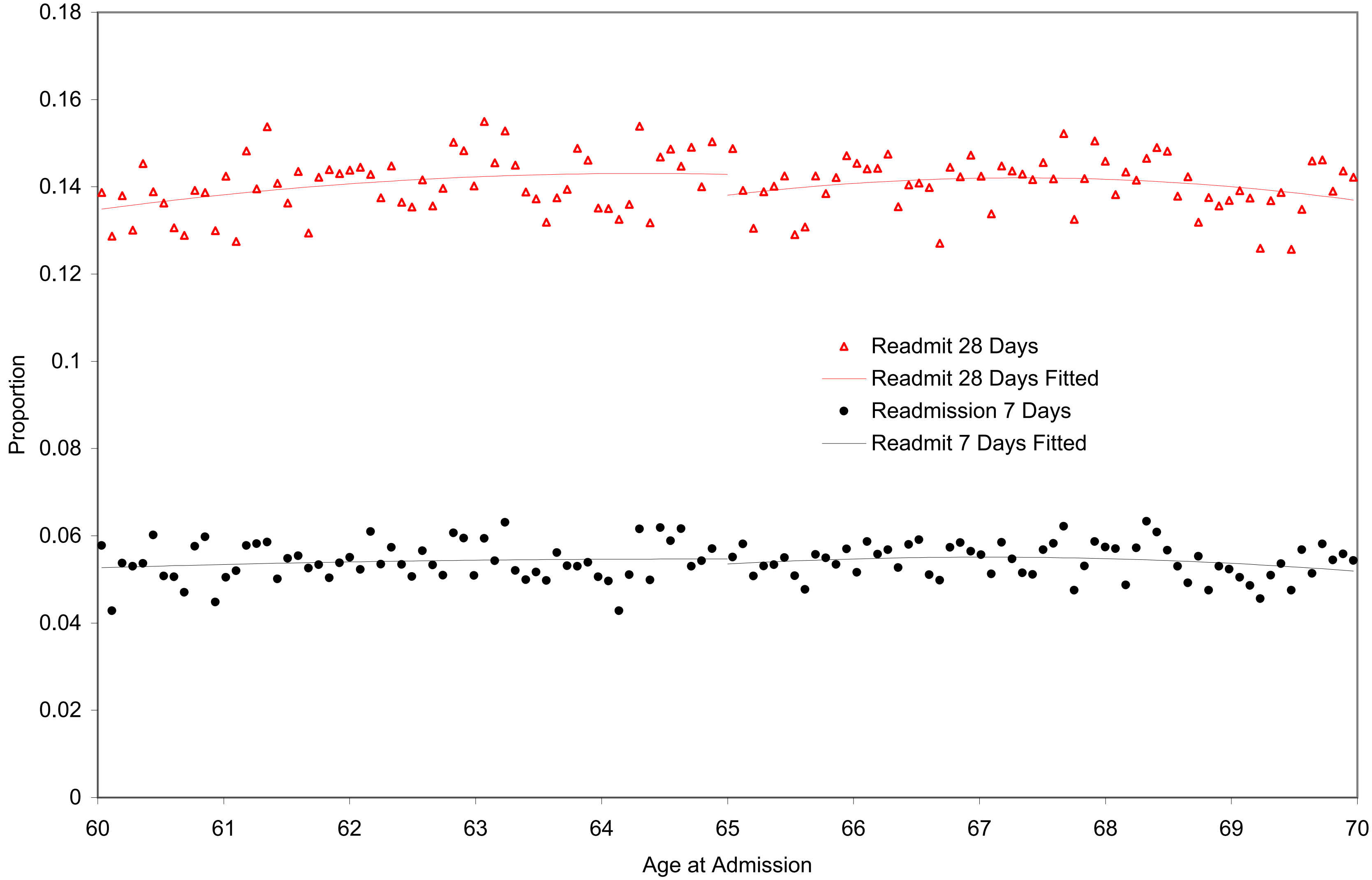
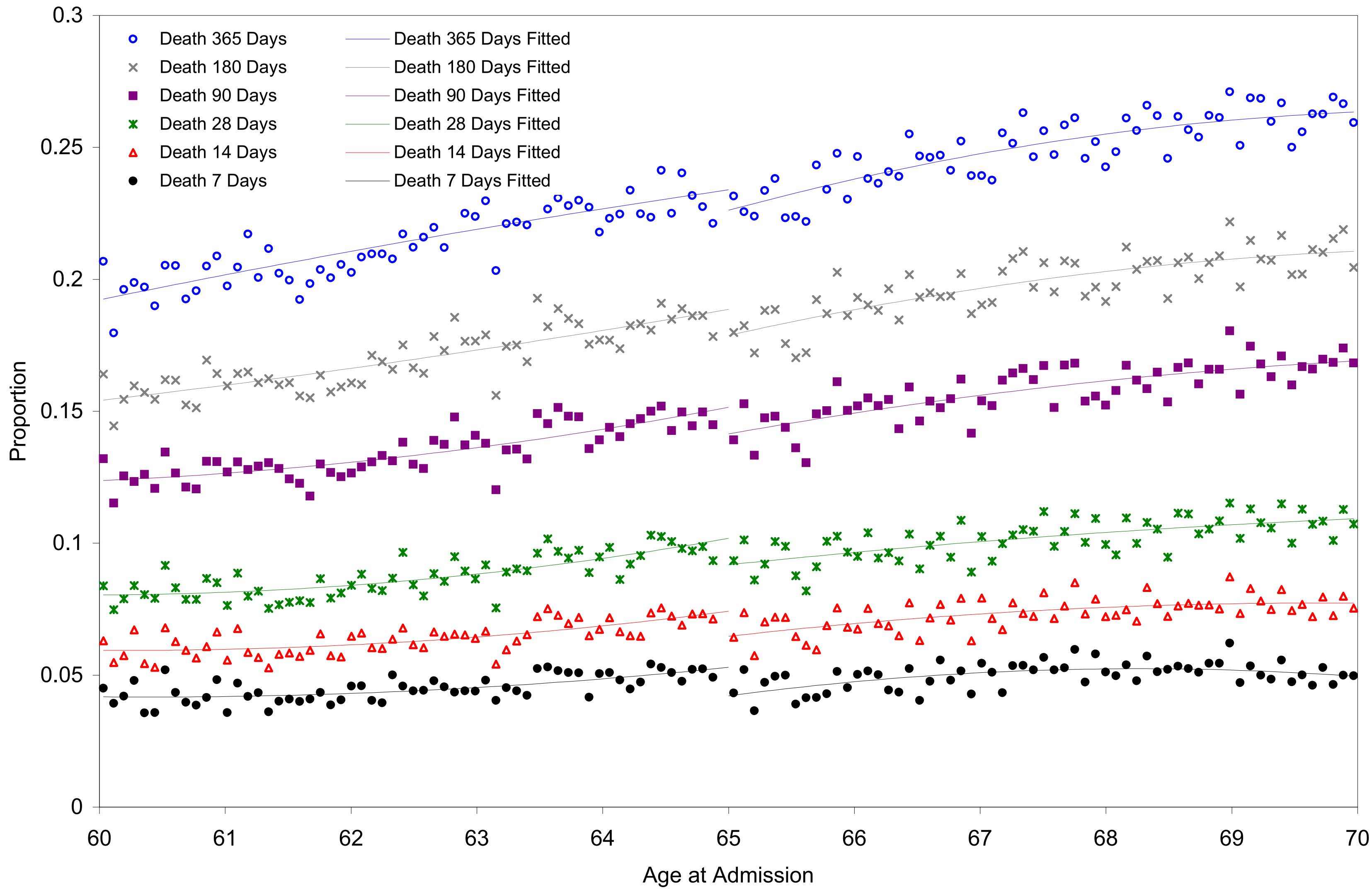


Figure 8: Readmitted to Hospital



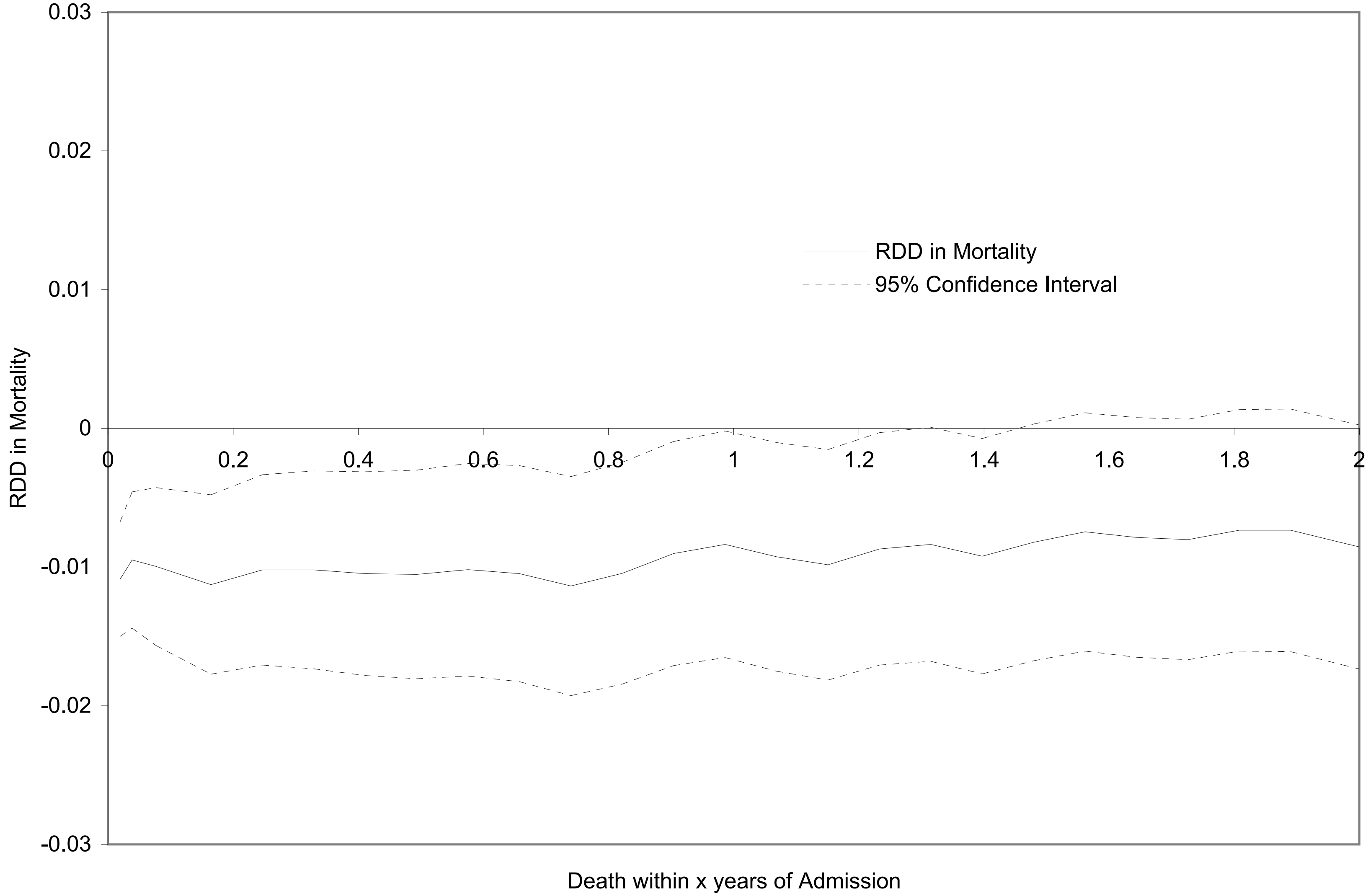
Notes: See notes from Figure 5. Days to readmission are computed from date of discharge.

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 the Group With Less Evidence of Selection

	ICD-9	Admissions	Length of Stay	Procedures	List Charges	Died	Transfer Across Hospital
Obstructive chronic bronchitis with acute exacerbation	491.21	61,601	6.25	1.21	23,749	0.030	0.029
Respiratory failure	518.81	24,376	13.79	3.72	65,315	0.228	0.100
Acute myocardial infarction of other inferior wall first episode	410.41	21,211	7.29	5.17	52,732	0.071	0.270
Acute myocardial infarction of other anterior wall first episode	410.11	15,752	7.92	5.37	57,065	0.106	0.258
Intracerebral hemorrhage	431	10,749	18.03	3.66	62,051	0.338	0.160
Chronic airway obstruction, not elsewhere classified	496	9,162	6.52	1.48	18,902	0.050	0.033
Fracture of neck of femur Intertrochanteric section	820.21	6,876	14.23	2.67	39,870	0.026	0.100
Cerebral artery occlusion, unspecified	434.9	5,845	15.38	3.71	27,354	0.083	0.145
Convulsions unknown Cause	780.39	5,326	5.28	1.25	21,755	0.015	0.044
Asthma, unspecified with status asthmaticus	493.91	5,121	4.65	1.10	15,743	0.010	0.018

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	0.11877	0.11911	0.0243	0.0256
	[0.00472]	[0.00533]	[0.00476]	[0.00496]
Dummy Age 64.91-65	N	Y	N	Y
Observations	3,652	3,652	3,652	3,652
R-Squared	0.87	0.87	0.81	0.81
Wald Statistic		0.040		1.140
	Weekend t-stat > 6.62		Weekend t-stat 2.54-6.62	
Age Over 65	0.03235	0.0328	0.03512	0.03553
	[0.01018]	[0.01063]	[0.00914]	[0.00972]
Dummy Age 64.91-65	N	Y	N	Y
Observations	3,652	3,652	3,652	3,652
R-Squared	0.39	0.39	0.53	0.53
Wald Statistic		0.030		0.040
	Weekend t-stat 0.96-2.54		Weekend t-stat < 0.96	
Age Over 65	0.02741	0.03103	0.00598	0.00716
	[0.00947]	[0.00980]	[0.00879]	[0.00939]
Dummy Age 64.91-65	N	Y	N	Y
Observations	3,652	3,652	3,652	3,652
R-Squared	0.63	0.63	0.52	0.52
Wald Statistic		2.010		0.210

Notes: These regressions are run on log counts of admission by age where age is measured in days. The sample is restricted to people that are admitted from home to California hospitals between Jan 1, 1992 and November 30, 2002. All the regressions include a second order polynomial in age fully interacted with a dummy for age greater than or equal to 65. For people admitted to the hospital up to 31 days before they turn 65 it is impossible to determine if they are eligible for Medicare without their DOB and date of admission neither of which we have.

Table 3: Regression Discontinuity Estimates of Changes in Treatment Intensity

	Medicare				Uninsured			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Age Over 65	0.43893	0.4727	0.4712	0.45181	-0.07422	-0.08047	-0.07993	-0.0778
	[0.00408]	[0.00413]	[0.00410]	[0.00568]	[0.00215]	[0.00234]	[0.00233]	[0.00328]
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	0.211	0.211	0.211	0.211	0.101	0.101	0.101	0.101
Observations	424,694	424,694	424,694	424,694	424,694	424,694	424,694	424,694
Wald Statistic		79.020		13.890		102.56		9.16
	Private				Medicaid			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Age Over 65	-0.24765	-0.26704	-0.26634	-0.25771	-0.10105	-0.10802	-0.1076	-0.09725
	[0.00406]	[0.00423]	[0.00419]	[0.00580]	[0.00324]	[0.00339]	[0.00337]	[0.00469]
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	0.450	0.450	0.450	0.450	0.212	0.212	0.212	0.212
Observations	424,694	424,694	424,694	424,694	424,694	424,694	424,694	424,694
Wald Statistic		411.880		2.450		295.220		7.460

Notes: All the regressions include a second order polynomial in age fully interacted with a dummy for age 65 or older. Regressions 2-4 all include a dummy variable for people admitted to the hospital the month before they turn 65 because their Medicare eligibility is impossible to determine without their DOB and date of admission to the hospital neither of which we have. The residual insurance category which accounts for 1.6% of the population also shows a substantial decline at age 65. These results are available on request.

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	0.37382	0.36238	0.37354	0.41249	0.08898	0.10247	0.11505	0.13379	0.02464	0.02688	0.02895	0.03487
	[0.23642]	[0.24910]	[0.24631]	[0.33084]	[0.03005]	[0.03067]	[0.02771]	[0.03812]	[0.01078]	[0.01104]	[0.00949]	[0.01307]
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	7.964	7.964	7.964	7.964	2.507	2.507	2.507	2.507	9.754	9.754	9.754	9.754
Observations	424,694	424,694	424,694	424,694	424,694	424,694	424,694	424,694	367,611	367,611	367,611	367,611
Wald Statistic		18.810		1.330		227.570		0.370		472.980		0.230

Notes: All the regressions the regressions include a second order polynomial in age fully interacted with a dummy for age 65 or older. Dropping the month before people turn 65 modestly increases the size of most of the estimates. 13.4% of charges are missing and there is a discrete 0.6% decline in the number of missing charges at age 65.

Table 5: 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	0.00219	0.00255	0.0039	0.00672	0.00921	0.00978	0.00953	0.00948
	[0.00238]	[0.00247]	[0.00236]	[0.00324]	[0.00190]	[0.00196]	[0.00191]	[0.00261]
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	0.070	0.070	0.070	0.070	0.037	0.037	0.037	0.037
Observations	424,694	424,694	424,694	424,694	424,694	424,694	424,694	424,694
Wald Statistic		51.750		0.980		33.450		1.200
	Readmission Within 7 Days of Discharge				Readmission Within 28 Days of Discharge			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Age Over 65	-0.00297	-0.00111	-0.00106	-0.00452	-0.00741	-0.00479	-0.00520	-0.00988
	[0.00213]	[0.00220]	[0.00219]	[0.00303]	[0.00325]	[0.00336]	[0.00332]	[0.00457]
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	0.055	0.055	0.055	0.055	0.143	0.143	0.143	0.143
Observations	424,694	424,694	424,694	424,694	424,694	424,694	424,694	424,694
Wald Statistic		13.870		1.430		24.890		1.120

Notes: All the regressions the regressions include a second order polynomial in age fully interacted with a dummy for age 65 or older. Dropping the month before people turn 65 modestly increases the size of most of the estimates.

Table 6: 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	-0.01109	-0.01086	-0.00985	-0.00728	-0.00997	-0.00947	-0.00816	-0.00729	-0.01053	-0.00993	-0.00835	-0.00595
	[0.00203]	[0.00210]	[0.00197]	[0.00271]	[0.00241]	[0.00250]	[0.00232]	[0.00319]	[0.00280]	[0.00290]	[0.00266]	[0.00365]
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	0.049	0.049	0.049	0.049	0.069	0.069	0.069	0.069	0.095	0.095	0.095	0.095
Observations	406,780	406,780	406,780	406,780	406,780	406,780	406,780	406,780	406,780	406,780	406,780	406,780
Wald Statistic		18.11		1.16		20.59		0.13		22.97		0.51

	Died Within 90 Days of Admission				Died Within 365 Days of Admission			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Age Over 65	-0.01105	-0.0101	-0.00804	-0.00824	-0.00985	-0.00877	-0.00645	-0.00385
	[0.00335]	[0.00347]	[0.00313]	[0.00429]	[0.00399]	[0.00413]	[0.00371]	[0.00509]
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	0.144	0.144	0.144	0.144	0.228	0.228	0.228	0.228
Observations	406,780	406,780	406,780	406,780	406,780	406,780	406,780	406,780
Wald Statistic		21.05		0.85		40.71		2.19

Notes: All the regressions the regressions include a second order polynomial in age fully interacted with a dummy for age 65 or older. The days to death are computed from the day of admission to the hospital. People with Missing SSNs can not be matched to the mortality data so they have been dropped from the regressions.

Table 7: Mortality within 28 Days by Route Into Hospital

	All	Elective	ER and Unplanned	ER and Unplanned (> 6.62)	ER and Unplanned (2.54-6.51)	ER and Unplanned (0.96-2.54)	ER and Unplanned (< 0.96)
Alpha	0.0654	0.1064	0.0250	0.0318	0.0343	0.0301	0.0071
Just Under 65 death rates	0.0510	0.0330	0.0683	0.0264	0.0735	0.0696	0.1018
Just Over 65 Death Rates	0.0464	0.0299	0.0637	0.0295	0.0673	0.0648	0.0918
RDD at 65 Point estimate	-0.0046	-0.0031	-0.0046	0.0031	-0.0061	-0.0048	-0.0099
Worst Case Bias	-0.0032	-0.0036	-0.0016	-0.0010	-0.0024	-0.0020	-0.0007
Lower Bound Estimate	-0.0014	0.0005	-0.0030	0.0040	-0.0037	-0.0027	-0.0093
Percent of Obs	1.00	0.50	0.50	0.11	0.13	0.12	0.12

Notes: The ranges below the ER Unplanned category are the range of t-statics on the ratio of weekend to weekday admissions of the conditions included in that column. Alpha is RDD/(1+RDD)

Table 8: Treatment Intensity and Outcomes by Insurance Status

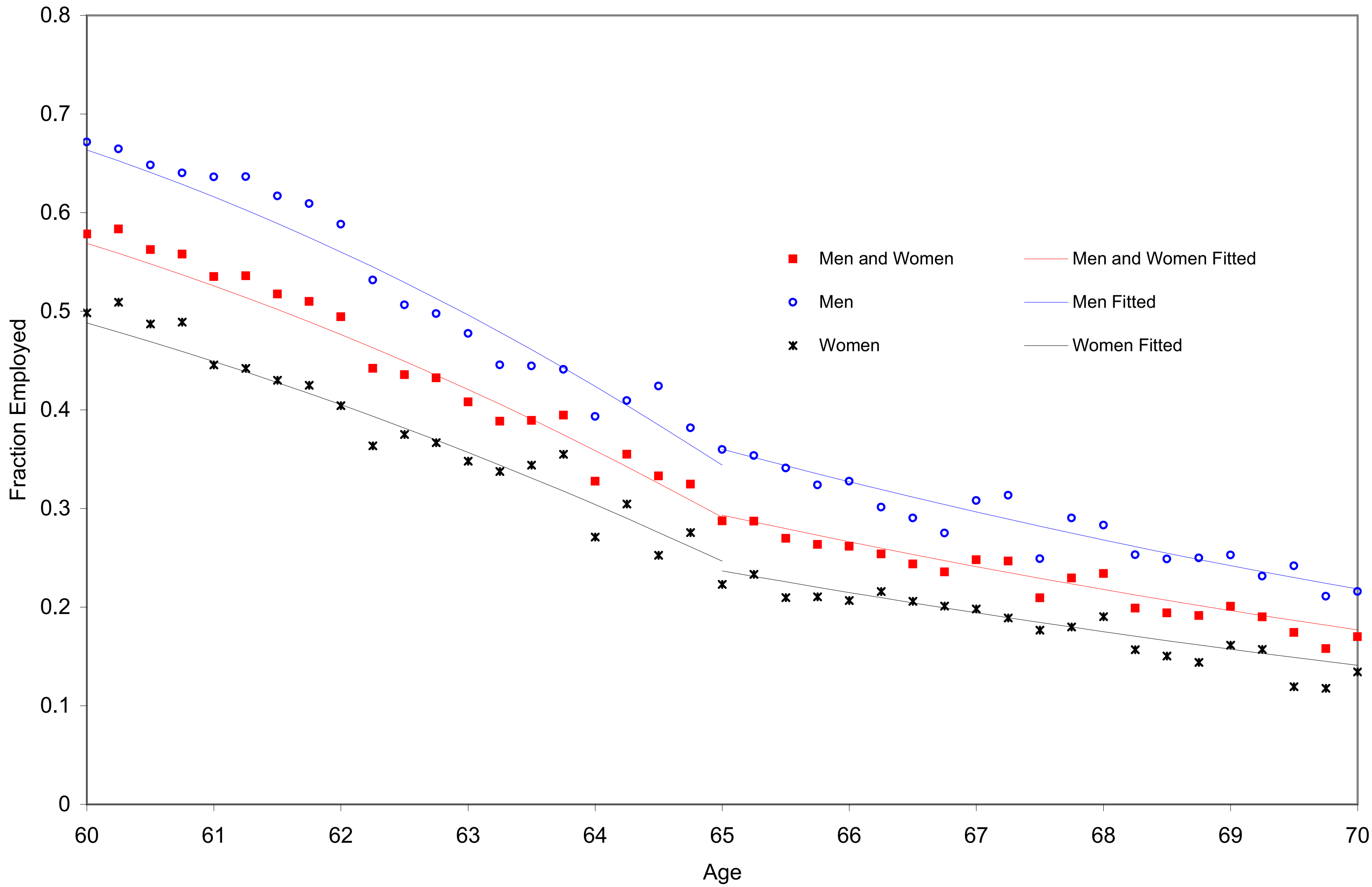
	Uninsured		Medicare		Private Insurance		Medicaid		Length of Stay		Procedure Count	
	High Insurance	Low Insurance	High Insurance	Low Insurance	High Insurance	Low Insurance	High Insurance	Low Insurance	High Insurance	Low Insurance	High Insurance	Low Insurance
Age Over 65	-0.05312	-0.10725	0.50409	0.44178	-0.35071	-0.18597	-0.08387	-0.13046	0.34836	0.39322	0.08693	0.12021
	[0.00285]	[0.00370]	[0.00577]	[0.00592]	[0.00616]	[0.00582]	[0.00421]	[0.00534]	[0.40856]	[0.28633]	[0.04356]	[0.04379]
Observations	212,033	212,661	212,033	212,661	212,033	212,661	212,033	212,661	212,033	212,661	212,033	212,661

	Log Charges		Readmission Within 7 Days		Readmission within 28 Days		Across Hospital Transfer		Within Hospital Transfer	
	High Insurance	Low Insurance	High Insurance	Low Insurance	High Insurance	Low Insurance	High Insurance	Low Insurance	High Insurance	Low Insurance
Age Over 65	0.02711	0.02466	-0.00036	-0.0019	-0.00269	-0.0067	0.0016	0.00315	0.00861	0.01108
	[0.01639]	[0.01539]	[0.00307]	[0.00315]	[0.00468]	[0.00483]	[0.00363]	[0.00337]	[0.00280]	[0.00274]
Observations	177,449	190,162	212,033	212,661	212,033	212,661	212,033	212,661	212,033	212,661

	Died Within 7 Days		Died Within 14 Days		Died Within 28 Days		Died Within 90 Days		Died Within 365 Days	
	High Insurance	Low Insurance	High Insurance	Low Insurance	High Insurance	Low Insurance	High Insurance	Low Insurance	High Insurance	Low Insurance
Age Over 65	-0.00941	-0.01236	-0.00752	-0.01151	-0.00756	-0.01246	-0.00471	-0.01586	-0.00673	-0.01105
	[0.00301]	[0.00295]	[0.00358]	[0.00350]	[0.00414]	[0.00405]	[0.00494]	[0.00488]	[0.00587]	[0.00584]
Observations	204,834	201,946	204,834	201,946	204,834	201,946	204,834	201,946	204,834	201,946

Notes: Robust standard errors in brackets. High Insurance is is people living in zip codes where the proportion of people 55-64 that are uninsured is between 0 and 0.0724450. The low insurance category is composed of people living in zipcodes where the range is from 0.0724450 to 1.

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

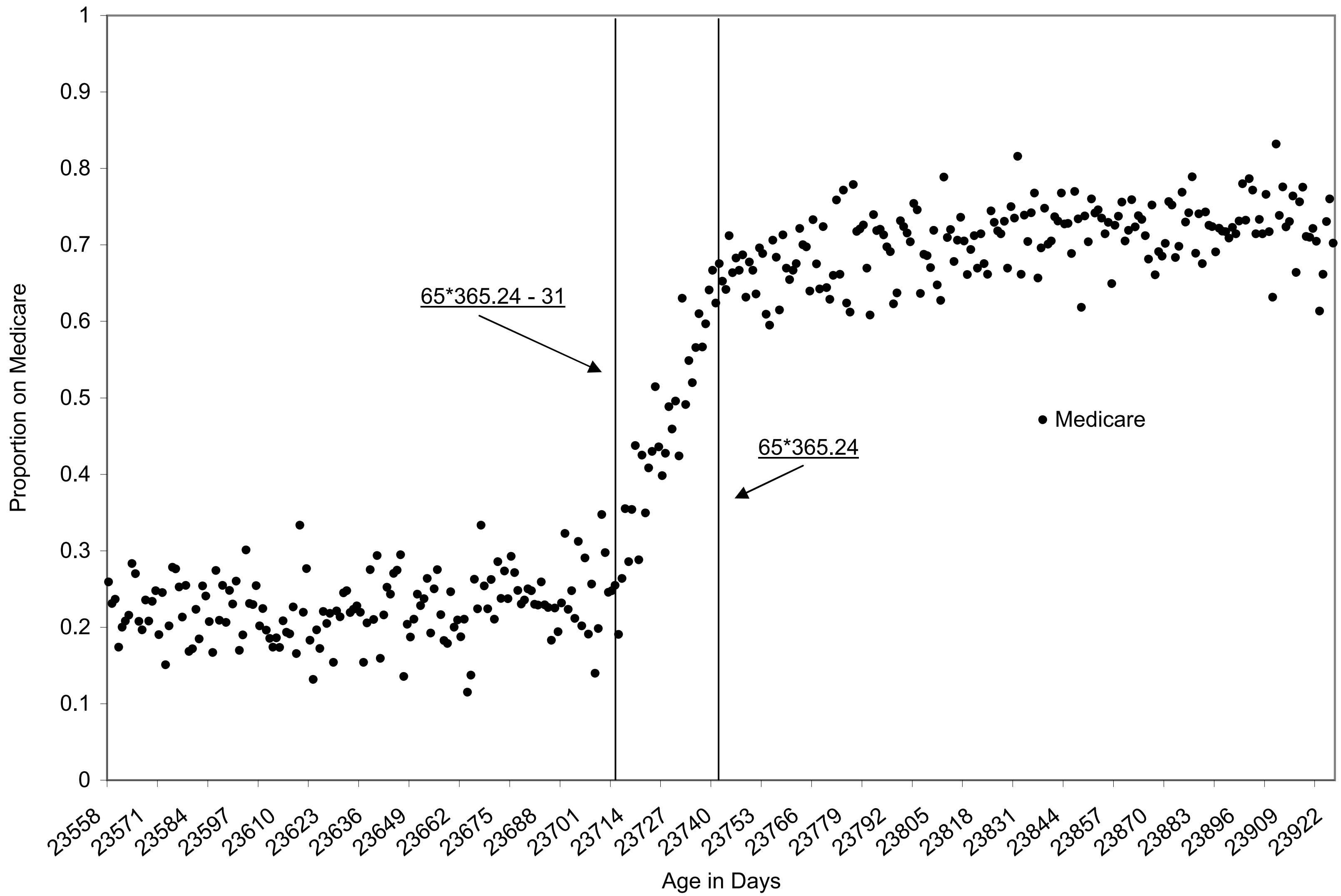


Appendix B: RDD in Admissions Estimated With a Cubic Polynomial

	Non ER or Planned		ER and Unplanned		Weekend t-stat > 6.62	
Age Over 65	0.11911	0.12911	0.0256	0.03805	0.0328	0.05663
	[0.00533]	[0.00787]	[0.00496]	[0.00676]	[0.01063]	[0.01426]
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	0.03553	0.04032	0.03103	0.04388	0.00716	0.02063
	[0.00972]	[0.01337]	[0.00980]	[0.01356]	[0.00939]	[0.01279]
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	0.53	0.53	0.63	0.63	0.52	0.52

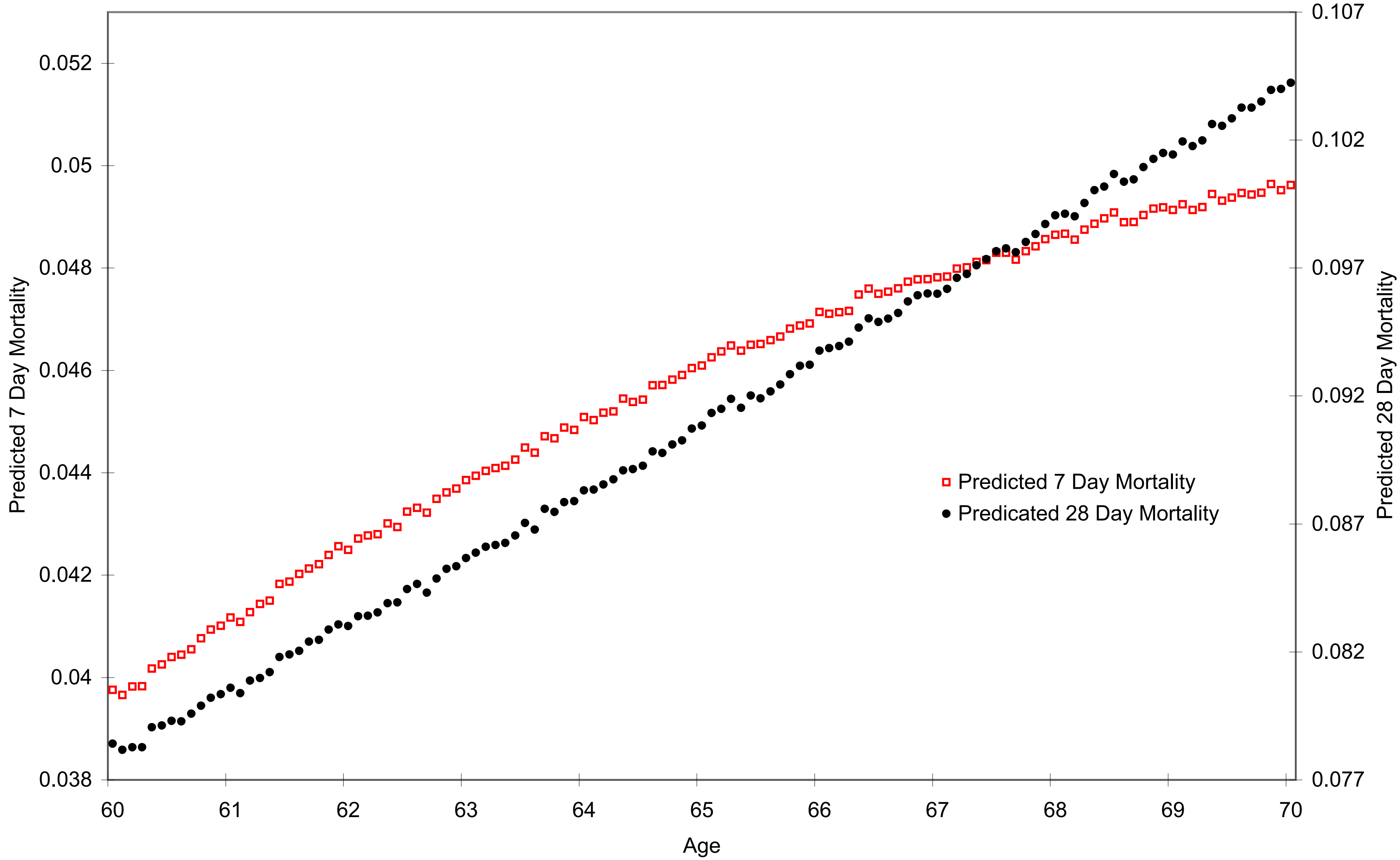
Notes: See notes from Table 2.

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.