

# WORKING P A P E R

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## The Impact of Health Insurance Status on Treatment Intensity and Health Outcomes

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LABOR AND POPULATION

# **The Impact of Health Insurance Status on Treatment Intensity and Health Outcomes**

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## **Abstract**

This paper uses the abrupt changes in health insurance coverage at age 65 arising from the Medicare program eligibility rules to evaluate the impact of insurance status on treatment intensity and health outcomes. Drawing from several million hospital discharge records for the State of California, we begin by identifying a subset of patients 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 who are just under 65 and those who are just over 65. The fraction of patients in this group who lack health insurance, however, falls sharply at age 65, while the proportion with Medicare as their primary insurer rises. Tracking health-related outcomes of the group, we find significant increases in treatment intensity at the age 65 barrier, including increases in the number of procedures performed, and total list charges. We also find a rise in the probability that patients are transferred to other units within the same hospital, coupled with a reduction in the probability of discharge to home. Finally, we estimate a drop in the rate of re-admission within one month of the initial discharge.

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Although there is an extensive literature on the differences in health-related outcomes between people with and without health insurance, and between people with different forms of insurance coverage, there is still considerable uncertainty over the fraction of these differences that are caused by insurance status.<sup>1</sup> Patients and their health care providers have incentives to increase the use of services when insurance coverage (or more generous coverage) is available, suggesting that coverage status could plausibly affect treatment intensity. To the extent that medical services affect health, there may also be an effect on health outcomes. Nevertheless, there are substantial legal and ethical barriers to treating patients differently depending on their insurance status.<sup>2</sup> Moreover, people with no insurance, or with less generous coverage, differ in ways that may exaggerate the true effects of insurance status.<sup>3</sup>

In this paper we use the abrupt shift in insurance status at age 65 that results from the eligibility rules of the Medicare program to develop new evidence on the effects of health insurance on the intensity of medical treatment provided in the hospital, and on health outcomes. We focus on admissions through the emergency room for serious medical conditions that have similar weekend and weekday admission rates. Due to staffing constraints, hospitals prefer to admit patients with “deferrable” conditions on weekdays. The conditions for which admission is

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<sup>1</sup> See Brown et al. (1998) and Levy and Meltzer (2001) for reviews of the effects of insurance on health care use and outcomes.

<sup>2</sup> For example, the federal Emergency Medical Treatment and Labor Act requires hospitals with emergency rooms to provide a minimum level of care to all patients regardless of ability to pay. In public opinion polls, three quarters of Americans agree with the statement that the amount and quality of health care should not depend on ability to pay (Harris Interactive (2003)).

just as likely on a weekend as a weekday are presumably “non-deferrable.” For patients with these non-deferrable conditions we argue that the decision to present at an emergency room is unlikely to depend on health insurance status. Consistent with this assertion, there is no evidence that the arrival rate of patients increases at age 65. This is in contrast to admissions for deferrable procedures like coronary bypass surgery, which show a 20 percent jump at the Medicare eligibility limit (Card, Dobkin, and Maestas, 2004).

Focusing on emergency room admissions for non-deferrable conditions, we turn to an analysis of the age profiles of various case 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 insurance coverage rises sharply, as does the fraction of patients who list Medicare as their primary insurer. The number of procedures performed in hospital and total list charges also increase at age 65, suggesting that the changes in insurance status affect treatment intensity. We also find a reduction in the probability that patients are discharged to their home at age 65, coupled with an increase in the probability of being transferred to another unit within the same hospital. Finally, the probability of being re-admitted within a month of discharge drops at age 65, consistent with the view that patients with no coverage, or with relatively limited coverage, are more likely to be discharged in an unhealthy condition. Taken as a whole, we believe the results indicate relatively large effects of insurance status on treatment intensity, and potentially important effects on health outcomes.

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<sup>3</sup> For example, people who lack insurance are less educated than those with insurance, and less likely to engage in “healthy” behaviors like regular exercise and seat belt use. See Card, Dobkin, and Maestas (2004, Table 1).

In the next section of the paper we present a brief overview of the existing literature on the impact of insurance status on health outcomes, and describe our regression-discontinuity research design. Section 3 provides a description of the data used in the analysis, and our procedures for identifying non-deferrable emergency room admissions. Section 4 presents our main analysis of the age profiles of treatment intensity for the sub-sample of non-deferrable admissions. Section 5 concludes.

## *II. Measuring the Causal Effects of Health Insurance Coverage*

### *a. Previous Studies*

In their recent review of the literature on health insurance and health-related outcomes, Levy and Meltzer (2001) draw a sharp distinction between observational studies and studies based on more rigorous research designs.<sup>4</sup> Observational studies typically compare health utilization and health outcomes between people with and without insurance coverage, adjusting for observed covariates. For example, Ayanian et al. (1993) compare survival rates of breast cancer patients with private insurance, Medicaid, and no insurance, and find higher death rates for the uninsured and Medicaid patients.<sup>5</sup> Even the best observational studies may be confounded by unobserved factors that simultaneously affect health, insurance status, and a

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<sup>4</sup> A similar point was made in the earlier review by Brown et al. (1998).

<sup>5</sup> More sophisticated longitudinal analyses are presented by Kasper et al. (2000), and Baker et al. (2001). The former use a two-year panel from the Kaiser Survey of Family Health Experiences to correlate changes in insurance coverage with changes in indicators of access to medical care, and changes in health. The latter compare changes in health between 1992 and 1996 for people in the Health and Retirement Study with differing insurance coverage patterns over the interval.

person's willingness or ability to utilize health care services. For this reason, Levy and Meltzer (2001) argue that reliable inferences about the effects of health insurance can only be drawn from experimental and quasi-experimental studies.

The only large scale randomized evaluation of the effects of health insurance, conducted by the RAND Corporation in the 1970s, compared the utilization of health care services, and health outcomes, for groups assigned to different insurance plans (Manning et al., 1987). The RAND experiment was not designed to evaluate insurance relative to no insurance.

Nevertheless, the results suggest that the type of insurance has a substantial effect on use of services, with greater expenditures by groups assigned to plans with lower co-insurance rates. These findings are potentially relevant for research designs based on comparisons around the Medicare eligibility age threshold, since the majority of people who enroll in Medicare at age 65 obtain supplemental coverage through a current/previous employer or a "Medigap" policy. The combination of Medicare and supplemental coverage may be more generous than a typical insurance package prior to 65, particularly with respect to co-payments and deductibles for in-hospital procedures. As we discuss in more detail below, this complicates the interpretation of comparisons between people just over and just under 65, since the over-65 group has fewer people with no insurance **and** more with relatively generous insurance coverage.

There have been a number of prominent quasi-experimental studies of the impact of insurance coverage on the use of health care services and health outcomes. One group of studies examines the effects of the Medicaid expansions on the insurance coverage and health-related outcomes of low-income mothers and children (e.g., Currie and Gruber (1996a, 1996b)). While

the Medicaid expansion had very modest effects on overall insurance coverage<sup>6</sup>, Currie and Gruber (1996a) find some evidence of a rise in use of services by children, while Currie and Gruber (1996b) argue they led to a significant decline in infant mortality.

More closely related to this paper is a series of studies on the effects of the Medicare program, including Lichtenberg (2001), Decker and Rapaport (2002), Decker (2002), McWilliams et al. (2003), and Dow (2004). Lichtenberg (2001) uses life tables constructed by the Social Security Administration (SSA) to test for a “trend break” in the age profile of mortality growth at age 65. Although his results show evidence of a break, subsequent analyses by Card, Dobkin and Maestas (2004) and Dow (2004) show that this is an artifact of the process used to construct the SSA life tables. Mortality rates in the SSA tables are smoothed within 5-year age intervals, then joined at the seams by osculatory interpolation, a method which smooths the age profile of mortality rates, but also induces artificial oscillations in the growth rate of mortality across the seams, and which leads to the impression of a trend break in the growth rate of mortality at 65 (and also at 55 and 60 - see Dow, 2004). Comparisons based on alternative data sources show less evidence of a shift in the age profile of mortality at age 65.<sup>7</sup>

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<sup>6</sup> Much of the literature on the Medicaid expansions has focused on whether the expansions crowded out other forms of coverage (e.g., Cutler and Gruber, 1996). See Card and Shore-Sheppard (2004) for an overview and attempt to reconcile conflicting findings on this question. Takeup rates for Medicaid coverage offered under the expansions are on the order of 10-20 percent.

<sup>7</sup> Dow (2004) also looks at the age profiles of mortality for cohorts who reached age 65 around the year of the introduction of Medicare, and finds some indication that the profiles of the cohorts who reached 65 after Medicare was available shifted down.

Dow (2004) uses National Health Interview Survey (NHIS) data from 1963 (3 years before the introduction of Medicare program) and 1970 (4 years after) to conduct a difference-in-differences analysis of the change in health-related outcomes for people between 66 and 75 years of age, relative to those between 55 and 64. His results suggest that the Medicare program increased insurance coverage among the over-65 age group by 12 percentage points, and also was associated with a relative rise in hospitalization rates. A potential problem with Dow's comparisons is their reliance on the assumption that health-related behaviors and outcomes of the pre-65 and post-65 groups would have moved in parallel between 1963 and 1970 in the absence of Medicare. Any differential trends for the two groups will confound his estimated effects.

The study by McWilliams et al. (2003) uses the longitudinal structure of the Health and Retirement Study (HRS) to examine changes in use of health care services from the period 1-2 years before reaching age 65 to the period 1-2 years after. The focus is on comparisons between people who had held health insurance coverage continuously before reaching age 65 (i.e., in both of the two previous HRS interviews before their 65th birthday), intermittently (in one of the two previous interviews), or were uninsured in both previous interviews. Despite the small sizes of the intermittent and uninsured groups (216 and 167 people, respectively), McWilliams et al. (2003) find that the relative use of medical screening procedures (cholesterol testing, mammography, prostate examination) increases after age 65 for the uninsured group relative to the other two groups. On the other hand, they find no evidence of a relative rise in rates of taking medication for arthritis or hypertension. These results suggest that the rise in health insurance coverage attributable to Medicare leads to some rise in use of medical care by previously uninsured people. It is less clear whether Medicare also affects the use of medical services by people who were previously insured.



The study by Decker and Rapaport (2002) uses a regression discontinuity research design to examine the age profiles of the probability of having a mammogram or clinical breast exam, and of having a “late stage” breast cancer diagnosis.<sup>8</sup> Consistent with the findings in McWilliams et al. (2003) they find that overall rates of breast cancer screening rise after age 65, with evidence of larger increases for less-educated women and black women. Since less-educated women and black women have larger gains in insurance coverage at age 65, these patterns are consistent with a positive effect of insurance coverage on screening rates. They also find some indication that breast cancers are less likely to be detected at a later stage once women reach the age of 65, although the pattern of effect sizes by race and education is less consistent with an insurance coverage channel. A potential concern with Decker and Rapaport’s (2002) results is their maintained assumption of a linear age profile for the various outcomes, with the same slope before and after age 65. Any nonlinearity in the underlying age profiles will confound their estimates of the discontinuities at age 65. Card, Dobkin, and Maestas (2004) present estimates from more flexible specifications and find less systematic evidence that Medicare eligibility is associated with increases in mammography or other preventative screenings.

A final study that attempts to measure the causal effects of health insurance coverage on in-hospital treatment intensity is Doyle (2005). Doyle uses data on severe automobile accident victims who were hospitalized as a result of their injury, collected by the Crash Outcome Data Evaluation System. Although this is an observational design, Doyle argues that the random nature of automobile accidents and the lack of discretion in presenting at the hospital eliminate

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<sup>8</sup> Decker and Rapaport (2002b) extend the analysis to consider the impacts of Medicare coverage on the probability of survival among breast cancer victims.

many of the biases in conventional observational studies of health care utilization by insurance status. His preferred specifications suggest that crash victims without insurance have about 15% shorter hospital stays and facility charges, and 40% higher mortality rates than those with private insurance. If valid, these results imply that lack of insurance coverage causes very large discrepancies in the intensity and quality of care. Nevertheless, it is unclear whether conditioning on a sample of accident victims actually reduces the biases that affect simple observational comparisons between insured and uninsured hospital patients.

### ***b. Regression Discontinuity-Based Design***

Our research design builds on the existing literature, while attempting to improve on some of the limitations of earlier studies. Specifically, we implement a regression-discontinuity analysis of treatment intensity and health-related outcomes around age 65 for patients admitted to the hospital for a set of non-deferrable conditions with similar weekend and weekday admission rates. In this section we outline our methods and present a simple framework for interpreting the estimation results.

As a starting point, we posit a simple causal model of the effect of health insurance coverage on the use of health care services for a sample of hospital patients:

$$(1) \quad y_i = X_i \alpha + f(a_i; X_i) + \sum_j C_{ij} \beta_j + \varepsilon_i,$$

where  $y_i$  is a measure of the quantity (or quality) of services used by patient  $i$ ,  $X_i$  is a set of observed characteristics of patient  $i$  (diagnosis, gender, race/ethnicity, home neighborhood, etc),  $a_i$  is the age of patient  $i$  (measured in days in our empirical analysis),  $f(a_i; X_i)$  represents a flexible but smooth age profile reflecting age-related differences in underlying health (which can

depend on  $X_i$ ),<sup>9</sup> the variables  $C_{ij}$  ( $j=1,2,\dots,J$ ) represent indicators for the type or generosity of insurance coverage held by patient  $i$ , and  $\varepsilon_i$  is a residual component reflecting unobserved determinants of  $y$ , such as the severity of illness or differences across health care providers. Studies of the effect of insurance coverage on the quantity or quality of health care services aim to provide causal estimates of the coverage status indicators (i.e., consistent estimates of the coefficients ( $\beta_j$ )). The major threat for an observational design (based on ordinary least squares or matching methods) is the possibility that coverage status is correlated with the unobserved factors  $\varepsilon_i$ .

Assuming that the distribution of unobserved factors is the same for people who are just under and just over 65, the sharp age limit for Medicare coverage at 65 provides a potential regression discontinuity research design for estimating at least some combination of the coverage coefficients.<sup>10</sup> To illustrate this point, Figure 1 presents the age profiles of health insurance coverage between ages 55 and 75, using data reported in the 1994-2004 March Current Population Surveys (CPS).<sup>11</sup> We graph the fractions of the population with each of four types of

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<sup>9</sup> For example, in our empirical analysis we assume that  $f(a; X)$  is a second order polynomial in age, with separate linear and quadratic terms on either side of the age 65 boundary. This specification allows the first and second derivatives of  $f(a; X)$  to change discontinuously at age 65.

<sup>10</sup> Regression discontinuity methods are described in Angrist and Krueger (1999).

<sup>11</sup> Medicare is not universal: an individual or their spouse must have a minimum of 40 quarters of covered employment to be eligible. Nevertheless, a very high fraction of the elderly population is eligible. Medicare is also available to individuals who are under 65 and receiving Disability Insurance (DI), or have late stage kidney disease. The fraction of the near elderly receiving DI has risen sharply over the past decade (Autor and Duggan, 2003). About 15% of the overall population of 64 year olds, and around 30% of the less-educated minority population were receiving Medicare through DI in the 1990s, according to data from the March Current Population Survey.

coverage: Medicare; private coverage (including employer-related or individually purchased coverage); Medicaid; and military-related coverage. (Note that people can be covered by two or more of these forms of insurance so the fractions add to more than 1). We also show the fraction with at least one form of insurance. At age 65, the fraction of people who report Medicare coverage jumps from 17% to 85%, while the fraction with any coverage rises from 85% to 98%.<sup>12</sup> By comparison, trends in private coverage, Medicaid coverage, and military-related coverage are all smooth, suggesting most people who have coverage before age 65 transition to a combination of Medicare and supplemental coverage once they reach 65.

To understand the implications of these patterns for the age profile of health care utilization described by equation (1), suppose that a person's health insurance coverage can be classified into three mutually exclusive categories: generous coverage ( $C_{i1}=1$ ); limited coverage ( $C_{i2}=1$ ); or no coverage (the reference category). Consider linear probability models for the events of generous or limited coverage of the form:

$$(2a) \quad C_{i1} = X_i \gamma_1 + g_1(a_i; X_i) + \text{Post65}_i \delta_1 + v_{1i},$$

$$(2b) \quad C_{i2} = X_i \gamma_2 + g_2(a_i; X_i) + \text{Post65}_i \delta_2 + v_{2i},$$

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<sup>12</sup> Alternative data sources give somewhat different estimates of the fraction of 60-64 year olds with any insurance. The National Health Interview Survey (NHIS) suggests coverage rates of around 90%—see Card, Dobkin and Maestas (2004). Both CPS and NHIS data show that Medicare coverage rates continue to rise between ages 65 and 70. Examination of CPS data for people who do not report Medicare coverage at age 66 shows that 83% have health insurance. Most of this group is still employed, which suggests they may not have yet filed for Medicare because they continue to obtain primary coverage through their employer.

where  $g_1(a_i ; X_i)$  and  $g_2(a_i ; X_i)$  are smooth age profiles and  $\text{Post65}_i$  is an indicator equal to 1 if individual  $i$  is over 65. Since  $C_{i1}$  and  $C_{i2}$  are mutually exclusive, these equations yield an implied model for the probability of **any** health care of the form:

$$(2c) C_{i1} + C_{i2} = X_i (\gamma_1 + \gamma_2) + g_1(a_i ; X_i) + g_2(a_i ; X_i) + \text{Post65}_i (\delta_1 + \delta_2) + v_{1i} + v_{2i} .$$

The age profile for the probability of any health insurance in Figure 1 suggests that there is positive jump at age 65, implying that  $\delta_1 + \delta_2 > 0$ . Moreover, to the extent that a combination of Medicare and supplemental coverage is more generous than the insurance coverage that most people have prior to age 65, there is also a discontinuous shift from limited to more generous coverage, implying that  $\delta_1 > 0$  and  $\delta_2 < 0$ .

Combining equations (2a) and (2b) with equation (1), the implied model for the age profile of the outcome  $y$  is:

$$(3) y_i = X_i (\alpha + \beta_1 \gamma_1 + \beta_2 \gamma_2) + h(a_i ; X_i) + \text{Post65}_i \pi + \xi_i ,$$

where

$$h(a_i ; X_i) = f(a_i ; X_i) + \beta_1 g_1(a_i ; X_i) + \beta_2 g_2(a_i ; X_i)$$

is a smooth function of age, the discontinuity at age 65 is

$$\pi = \beta_1 \delta_1 + \beta_2 \delta_2 ,$$

and the residual component is

$$\xi_i = \varepsilon_i + \beta_1 v_{1i} + \beta_2 v_{2i} .$$

Thus, to the extent that health insurance status has a causal effect on the outcome  $y$ , discontinuities in the probabilities of generous or limited health insurance coverage will generate a discontinuity in the age profile of health care utilization.

The discontinuity in the age profile of outcome  $y$  at age 65 reflects a combination of the relative size of the discontinuities in the probabilities of generous or limited insurance (i.e.,  $\delta_1$

and  $\delta_2$ ) and the effects of these two types of coverage on the outcome (i.e.,  $\beta_1$  and  $\beta_2$ ). Note that if  $\beta_1 = \beta_2 = \beta$ , then all that matters is whether the individual has **any** insurance coverage. In this case,  $\pi = \beta(\delta_1 + \delta_2)$ , which is proportional to the size of the (observable) discontinuity in the probability of any coverage at age 65. An estimate of  $\beta$  therefore can be recovered from the ratio of the discontinuities in the outcome  $y$  and the probability of any health care coverage.<sup>13</sup> At the opposite extreme, suppose that all that matters for outcome  $y$  is whether an individual has **generous** insurance coverage (i.e.,  $\beta_2 = 0$ ). In this case,  $\pi = \beta_1 \delta_1$ , which is proportional to the size of the jump in the probability of generous coverage. Unfortunately, it is difficult to accurately measure this jump in the absence of detailed data on the insurance policy (or policies) held by an individual.

In this paper we do not attempt to formally identify the separate effects of any insurance coverage and more generous coverage on the intensity of treatment or on measures of health status. Rather, we focus on obtaining credible estimates of the discontinuities in these outcomes, recognizing that they can arise either through a simple coverage effect, or through a generosity of coverage effect.

### ***Potential Problems for a Regression Discontinuity Approach***

As formalized by Lee (forthcoming 2005), the key assumption underlying a regression discontinuity approach is that within the sub-sample of people who are just under or just over the discontinuity (in our context, no more than a few weeks older or younger than their 65th

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<sup>13</sup> Equivalently,  $\beta$  can be estimated by two-stage least squares applied to equation (1), using Post65 as an instrument for coverage.

birthday), assignment to either side of the threshold is as good as random. This condition guarantees that

$$(4a) \quad E[ \varepsilon_i \text{ Post65}_i \mid X_i, f(a_i ; X_i) ] = 0 \quad \text{and}$$

$$(4b) \quad E[ v_{ij} \text{ Post65}_i \mid X_i, f(a_i ; X_i) ] = 0 \quad (j=1,2),$$

which are in turn sufficient conditions to ensure that the  $\delta$  coefficients in equations (2a) and (2b) and the coefficient  $\pi$  in equation (3) can be consistently estimated by conventional regression methods.

In a sample of hospital admission records the assumption that patients close to age 65 are “as good as randomly assigned” to either side of the age threshold is unlikely to be true if insurance status has any effect on the probability of being included in the sample. Since patients and health care providers are more likely to consider treatment if insurance is available, or if more generous coverage is available, it seems plausible that more patients, with less severe conditions, enter the hospital for treatment after age 65 (when Medicare coverage becomes available) than before. Consistent with this conjecture, Card, Dobkin, and Maestas (2004) show that hospitalization rates rise discretely at age 65 for many diagnoses, including chronic ischemic heart disease, chronic bronchitis, and osteoarthritis. Even for patients whose primary admission diagnosis is acute myocardial infarction there are roughly 5 percent more patients who are just over age 65 than just under 65 in samples of admission records from California and Florida.

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.<sup>14</sup> We select a set of non-deferrable conditions

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<sup>14</sup> This is similar in spirit to Doyle’s (2005) focus on patients who are hospitalized as a result of automobile accidents.

with relative weekend/weekday admission rates (though the ER) of 2/5. We then test the assumption that there is no remaining selection bias associated with the age 65 boundary using two tests. First, we test that there is no discontinuity in the number of admissions at age 65. Second, we test for discontinuities in the characteristics of patients, including the fractions with different diagnoses, and their demographic composition. Although such tests can never “prove” that there is no remaining selection bias, they impose a reasonably high standard and provide some confidence in the validity of our inferences.

Another potential problem in regression discontinuity designs is that other factors may change discretely at the discontinuity threshold. A specific concern with age 65 is that this is the traditional retirement age. By focusing on non-deferrable ER admissions we believe that confounding due to employment status is unlikely to be a problem. In any case, we show below that there are no discontinuities at age 65 in a wide variety of characteristics of the overall population, including employment status and family income. Recommended medical practices may also shift at age 65. For example, the U.S. Surgeon General has recommended different influenza vaccination policies for people over and under 65 (National Foundation for Infectious Disease, 2002), and during the vaccine shortage of 2004/2005 people over age 65 were prioritized to receive vaccinations. Again, however, we think this is unlikely to affect the characteristics or treatment of patients admitted through the ER for non-deferrable conditions.

### ***III. Data***

We use hospital discharge data from the State of California. The sample includes records for all patients discharged from hospitals regulated by the State of California between January 1, 1992 and December 31, 2002. To be included in the data a patient must have been admitted to



the hospital; thus, patients who were sent home after treatment in the emergency room do not appear in our sample.<sup>15</sup> In addition, discharges from a small number of hospitals under federal oversight, such as those on military bases, are not included in the data.

We trim this overall sample in two ways. First, we drop discharge records for patients admitted before January 1, 1992, since these admissions will only be captured if they involved a relatively long stay in the hospital. Second, we drop all discharge records for patients admitted on or after December 1, 2002, since these records will disproportionately represent shorter hospital stays (we have no record for patients who were admitted in December 2002 but were still in the hospital on December 31). The vast majority of patients admitted before November 30, 2002 were discharged by the end of December. Dropping these two groups of patients reduces our sample by about 1.1% and has almost no impact on our regression estimates.

The dataset has demographic information about the patient including age, race, ethnicity, gender and zip code of residence. The dataset also includes details about the patient's medical condition and treatment, such as principle cause of admission, up to 24 additional diagnoses, procedures performed, route of admission into the hospital, and disposition of the admission. In addition, the dataset contains a scrambled version of the patient's Social Security Number (known as an RLN) and the patient's exact birthday and date of admission. These variables make it possible to track patients who are transferred either across or within hospitals.

We track patients that are transferred either within or across hospitals, since any slippage in tracking patients across hospital stays will lead us to underestimate the impact of insurance on treatment intensity. In our data, 96% of patients have a valid RLN. For these patients, we use

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<sup>15</sup> 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.

the RLN in combination with the patient's age to search for matching records. Patients who are admitted to a hospital on the exact day that they are discharged from another hospital are coded as a readmission (and their records are combined into a single event). We track patients for up to 25 sequential stays in the hospital -- the maximum number of sequential stays in our data.

It is also important to track the 4% of patients with a missing RLN, since there is a 1 percentage point drop in the proportion with a missing RLN at age 65. For each patient with a missing RLN, we look for a subsequent admission to the hospital of someone the exact same age, gender and from the same residential zip code as the patient who was discharged. Matching on these variables resulted in only 95 duplicate matches, suggesting that this set of variables is sufficient to distinguish individuals in most cases. Again, we combined sequential admissions into a single record.

## ***VI. Results***

### **a. Preliminary Issues**

To illustrate the limitations of observational studies and motivate our quasi-experimental design, Table 1 presents a comparison of the insured and uninsured near elderly across several observable characteristics. The data are drawn from the 1997-2001 NHIS and the 1998-2002 Behavioral Risk Factor Surveillance System (BRFSS). As has been noted by many others (e.g., Mills and Bandhari, (2003)), the uninsured are of lower socio-economic status, engage in less healthy behaviors like smoking, and are in worse health. These observable differences suggest that the insured and uninsured also differ systematically across unobservable determinants of health outcomes, which implies observational comparisons might lead to biased estimates of the impact of insurance, even after controlling for observable characteristics.

As noted, a potential problem with using the transition to Medicare as a source of variation in insurance status is that other factors may change at age 65, including employment status and family income (which could affect treatment intensity if ability to pay has an effect on use of medical services). Card, Dobkin, and Maestas (2004) present evidence from the Current Population Survey (CPS) that the age profile in employment rates, family income, marital status, and residential mobility all trend smoothly through the age 65 threshold. We reproduce this evidence in Table 2, which shows regression-discontinuity estimates of the effect of reaching the Medicare eligibility age on several potential confounding variables following a flexible specification of equation (3).

#### **b. Constructing a Non-Selective Sample of Admissions**

A significant concern when comparing treatment intensity and outcomes for people who have been admitted to the hospital is that insurance status may directly affect the composition of the groups being compared. In Figure 2 we present the age profiles of the log of hospital admissions. The figure reveals a very large increase in non-emergency admissions at age 65 and a smaller increase in admissions through the emergency room. The additional admissions that occur after age 65 are likely to be systematically different than the rest of admissions, and in particular may include relatively more patients with less severe conditions. If so, this compositional change would bias our estimates of the impact of insurance.

To overcome this selection issue, we develop a method of identifying a subset of conditions sufficiently severe that individuals who present at the emergency room will be admitted to the hospital regardless of insurance status. Due to staffing constraints hospitals prefer to admit patients on weekdays. We identify non-deferrable conditions by calculating the

proportion of admissions in a 5-digit ICD-9 that occur on the weekend, noting that admissions for non-deferrable conditions should be just as likely to fall on a weekend as a weekday, and therefore have weekend proportions near  $2/7$  (.286). In Figure 3 we show the distribution of the proportion of weekend admissions in each ICD-9 for three groups of admissions: all admissions, ER admissions, and a subset of ER admissions in ICD-9s whose weekend proportion is near  $2/7$ . For all admissions, the distribution is notably skewed left, indicating substantial selection in favor of weekday admissions. In contrast, the distribution for all ER admissions is clearly centered around  $2/7$ , but still appears somewhat skewed left. To further reduce selection in the sample of ER admissions, we calculate the t-statistic of the difference between the proportion of ER weekend admissions in an ICD-9 and  $2/7$ , then select admissions in ICD-9s whose t-statistic is less than .965 in absolute value. Figure 3 illustrates how this method yields a distribution fairly tightly centered around  $2/7$ .

Figure 4 verifies that this subset of admissions shows little evidence of selection by graphing the age profile of log admissions in each quartile of the t-statistic for the difference from  $2/7$ . The top two quartiles with weekend proportions furthest from  $2/7$  show clear evidence of an increase in admissions at age 65, whereas the lowest quartile ( $|t| < .965$ ) shows no visible evidence of an increase in admissions. Finally, we present in Table 3 regression discontinuity estimates of the impact of reaching the Medicare eligibility age on log admissions of different types following a flexible specification of equation (3). We estimate an 11.9% jump in non-ER admissions and a 2.4% jump in ER admissions. In the lower panel of the table we present the regression discontinuity estimates for admissions in the t-statistic quartiles shown in Figure 4. These estimates confirm that conditions for which weekend admission proportions are nearest  $2/7$  ( $|t| < .965$  in column 7) show no statistically significant evidence of an increase in admissions

at age 65. The estimates in column 8 indicate that the fraction of this group with no insurance nevertheless declines sharply at 65, confirming the validity of our research design for this group. In the analyses that follow, we restrict our study to this group of admissions.

In Table 4 we display the average characteristics of admissions for the 10 most common conditions in our study group. Because our study group is characterized by non-deferrable conditions, the top 10 conditions are relatively severe, involving major heart problems, stroke, or respiratory problems. For each condition, we show the average length of stay, number of procedures performed, list charges, fraction who die in the hospital, and the fraction transferred across hospitals. There are very significant differences in these measures across conditions, which suggests we should include condition-level fixed effects in our analyses.

### **c. Changes in Treatment Intensity At Age 65**

We next analyze whether changes in insurance status arising from Medicare eligibility result in changes in treatment intensity. We examine three measures of treatment intensity: length of stay, number of procedures performed, and hospital list charges. In Figure 5A we present the age profile in length of stay for admissions in our study group. Although we use age in days in our estimation models, points on the figure represent averages over 30.43 days of age in order to make the figure more interpretable. Length of stay includes days spent at other hospitals if a patient is transferred. The fitted regression line in the figure comes from estimating a flexible specification of equation (3) that includes a second order polynomial in age (rescaled to 0 at 65) fully interacted with a dummy variable for age 65 and older. By interacting the polynomial with the age 65 dummy, we allow both the first and second derivatives of the age profile to change discontinuously at 65. The figure reveals that this specification fits the profile

in length of stay well. The fitted line shows a small and statistically insignificant increase in length of stay for people admitted after they turn age 65. In Figure 5B we present the age profile in the number of procedures a patient receives. The procedures include any diagnostic or surgical procedure that the patient receives during their hospital stay. The figure shows evidence of a sharp increase in the number of procedures performed on patients admitted at age 65, though there is variation around the fitted line. In Figure 5C we present the age profile in log hospital list charges. Hospital list charges may differ from actual charges paid because insurers have negotiated discounts with hospitals. In addition, list charges do not include many other costs such as physician fees, and are not reported for managed care patients. For example Kaiser Foundation Hospitals do not report list charges because they receive a constant capitated payment from each member whether or not the member is hospitalized. Despite these limitations, list charges should give some insight into changes in treatment intensity. The figure shows a discernible jump in list charges at age 65.

In Table 5 we present the regression results corresponding to Figures 5A-5C. We estimate a 3.9% percent increase in the average number of procedures performed at age 65, a 2.6% increase in list charges, and a 4.6% increase in length of stay, which is not statistically significant. The last set of regressions test for a discontinuity at age 65 in the proportion of admissions without charge data. We estimate a very small decrease in the proportion without charge data at age 65 and conclude this is unlikely to confound our estimates. The different model specifications show the regression estimates are very robust to the inclusion of year, month, weekend, gender and race dummies, as well as condition level fixed effects. This is evidence that observable covariates are balanced right around the age 65 threshold, and suggests

selection is probably not a significant problem. The inclusion of the condition level fixed effects increases the precision of our estimates.

We next examine patterns of case disposition by comparing the probabilities that a patient will be transferred to another hospital, another unit within the same hospital, or discharged home. In Figure 6A we show the age profile in the proportion of admissions that are discharged home from the first hospital unit they are admitted to. The figure reveals an abrupt decline in the proportion of patients that are discharged home. Figure 6B presents the age profile in the proportion of admissions that are transferred to another hospital, and shows evidence of what may be a slight increase in across-hospital transfers at age 65. In contrast, Figure 6C shows a sharp jump in the proportion of patients that are transferred to another unit *within* the same hospital at age 65.

Table 6 presents the regression discontinuity estimates corresponding to Figures 6A-6C. We estimate a 2.6% drop in the probability of being discharged home at age 65 (1.7 percentage points on a base of .639), compared to a 9% increase in the probability of being transferred to either another hospital or another unit within the same hospital. When we separate across-hospital transfers and within-hospital transfers, we find that most of the transfer effect is driven by within-hospital transfers, which jump by 19% at age 65. Across-hospital transfers increase by 5% but the estimate is not statistically significant.

#### **d. Effects on Health**

In order to understand how these changes in treatment intensity and disposition of admissions might impact health outcomes, we examine the effect of reaching the Medicare eligibility age on the probability of being readmitted to the hospital within 28 days of initial

discharge, and the probability of dying in the hospital. Figure 7 displays the age profile in readmission, which suggests a small reduction in the probability of readmission among patients admitted after age 65. Table 7 confirms that this is a statistically significant drop of 5.5%. When we shorten the readmission window to one day and one week, we find smaller and statistically insignificant effects. Figure 8 suggests a small reduction in the proportion of patients dying within the hospital at age 65, but Table 7 shows that the estimated effect of about 3.5% is not statistically significant. Interestingly, the pattern of coefficients across model specifications indicates less robustness to the inclusion of condition level fixed effects, and consequently covariates that are less well balanced around the age 65 threshold. Given that the readmission probabilities reveal that less well insured patients appear to be discharged prematurely our inability to observe deaths that occur outside the hospital is a significant limitation.

## ***V. Conclusions***

In this paper, we use the discrete change in health insurance coverage generated at age 65 by the rules of the Medicare program to identify the causal effect of insurance on hospital treatment intensity, case disposition, and health outcomes. We base our findings on a subset of non-deferrable emergency room admissions in California for which we find no evidence that the probability of admission (and therefore the probability of appearing in our data) varies with insurance coverage.

Our analyses show that insurance coverage has a significant causal effect on treatment intensity, case disposition, and health outcomes. We find that uninsured patients receive less intensive treatment and are more likely to be discharged home rather than transferred to another



hospital or unit within the same hospital for continued care. Coupled with our finding that the probability of being readmitted to the hospital within a month of discharge drops at age 65, our results are consistent with the possibility that patients with no coverage, or relatively limited coverage, are more likely to be discharged from the hospital in an unhealthy condition.

Federal law requires that hospitals admit and stabilize patients with life threatening conditions. It does not require that patients receive all necessary care or that they be transferred to the most appropriate treatment setting. We find that patients and their healthcare providers increase their use of hospital services when insurance coverage (or more generous coverage) is available, and that these additional hospital services appear to produce better health outcomes.

## References

"Fundamental Health Care Values," *Harris Interactive Health Care News*. 2003.

**Angrist, Joshua D and Krueger, Alan B.** "Empirical Strategies in Labor Economics," O. Ashenfelter and D. Card, *Handbook of Labor Economics*, 3A. Amsterdam, New York and Oxford: Elsevier Science, North-Holland, 1999.

**Autor, David H and Duggan, Mark G.** "The Rise in the Disability Rolls and the Decline in Unemployment." *Quarterly Journal of Economics*, 2003, 118(1), pp. 157-205.

**Ayanian, J. Z.; Kohler, B. A.; Abe, T. and Epstein, A. M.** "The Relation between Health Insurance Coverage and Clinical Outcomes among Women with Breast Cancer." *N Engl J Med*, 1993, 329(5), pp. 326-31.

**Baker, D. W.; Sudano, J. J.; Albert, J. M.; Borawski, E. A. and Dor, A.** "Lack of Health Insurance and Decline in Overall Health in Late Middle Age." *N Engl J Med*, 2001, 345(15), pp. 1106-12.

**Brown, M. E.; Bindman, A. B. and Lurie, N.** "Monitoring the Consequences of Uninsurance: A Review of Methodologies." *Med Care Res Rev*, 1998, 55(2), pp. 177-210.

**Card, David; Dobkin, Carlos and Maestas, Nicole.** "The Impact of Nearly Universal Insurance Coverage on Health Care Utilization and Health: Evidence from Medicare," National Bureau of Economic Research, Inc, NBER Working Papers, 2004.

**Currie, Janet and Gruber, Jonathan.** "Health Insurance Eligibility, Utilization of Medical Care, and Child Health." *Quarterly Journal of Economics*, 1996a, 111(2), pp. 431-66.

\_\_\_\_\_. "Saving Babies: The Efficacy and Cost of Recent Changes in the Medicaid Eligibility of Pregnant Women." *Journal of Political Economy*, 1996b, 104(6), pp. 1263-96.

**Decker, Sandra.** "Disparities in Access to Health Care for Older Americans before and after Medicare," *International Longevity Center*. New York, NY, 2002.

**Decker, Sandra and Rapaport, Carol.** "Medicare and Disparities in Women's Health," National Bureau of Economic Research, Inc, NBER Working Papers: 8761, 2002.

**Dow, William H.** "The Introduction of Medicare: Effects on Elderly Health," University of California, Berkeley, 2004.

**Doyle, Joseph J, Jr.** "Health Insurance, Treatment and Outcomes: Using Auto Accidents as Health Shocks," National Bureau of Economic Research, Inc, NBER Working Papers, 2005.

**GAO.** "Hospital Emergency Departments: Crowded Conditions Vary among Hospitals and Communities," United States General Accounting Office, 2003.

**Kasper, J. D.; Giovannini, T. A. and Hoffman, C.** "Gaining and Losing Health Insurance: Strengthening the Evidence for Effects on Access to Care and Health Outcomes." *Med Care Res Rev*, 2000, 57(3), pp. 298-318; Discussion 19-25.

**Lee, David.** "Randomized Experiments from Non-Random Selection in U.S. House Elections." *Journal of Econometrics*, forthcoming 2005.

**Levy, Helen and Meltzer, David.** "What Do We Really Know About Whether Health Insurance Affects Health?" *Unpublished Working Paper, JCPR Working Paper 275*, 2001.

**Lichtenberg, Frank R.** "The Effects of Medicare on Health Care Utilization and Outcomes." *Frontiers in Health Policy Research*, 2001, 5(1), pp. 27-52 (26).

**Manning, W. G.; Newhouse, J. P.; Duan, N.; Keeler, E. B.; Leibowitz, A. and Marquis, M. S.** "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment." *The American Economic Review*, 1987, 77(3), pp. 251-77.

**McWilliams, J. M.; Zaslavsky, A. M.; Meara, E. and Ayanian, J. Z.** "Impact of Medicare Coverage on Basic Clinical Services for Previously Uninsured Adults." *Journal of the American Medical Association*, 2003, 290(6), pp. 757-64.

**Mills, Robert J. and Bhandari, Shailesh.** "Health Insurance Coverage in the United States: 2000," Washington DC: GPO: United States Department of Commerce Bureau of the Census, Current Population Reports, 2003, 60-233.

## References

"Fundamental Health Care Values," *Harris Interactive Health Care News*. 2003.

**Angrist, Joshua D and Krueger, Alan B.** "Empirical Strategies in Labor Economics," O. Ashenfelter and D. Card, *Handbook of Labor Economics*, 3A. Amsterdam, New York and Oxford: Elsevier Science, North-Holland, 1999.

**Autor, David H and Duggan, Mark G.** "The Rise in the Disability Rolls and the Decline in Unemployment." *Quarterly Journal of Economics*, 2003, 118(1), pp. 157-205.

**Ayanian, J. Z.; Kohler, B. A.; Abe, T. and Epstein, A. M.** "The Relation between Health Insurance Coverage and Clinical Outcomes among Women with Breast Cancer." *N Engl J Med*, 1993, 329(5), pp. 326-31.

**Baker, D. W.; Sudano, J. J.; Albert, J. M.; Borawski, E. A. and Dor, A.** "Lack of Health Insurance and Decline in Overall Health in Late Middle Age." *N Engl J Med*, 2001, 345(15), pp. 1106-12.

**Brown, M. E.; Bindman, A. B. and Lurie, N.** "Monitoring the Consequences of Uninsurance: A Review of Methodologies." *Med Care Res Rev*, 1998, 55(2), pp. 177-210.

**Card, David; Dobkin, Carlos and Maestas, Nicole.** "The Impact of Nearly Universal Insurance Coverage on Health Care Utilization and Health: Evidence from Medicare," National Bureau of Economic Research, Inc, NBER Working Papers, 2004.

**Currie, Janet and Gruber, Jonathan.** "Health Insurance Eligibility, Utilization of Medical Care, and Child Health." *Quarterly Journal of Economics*, 1996a, 111(2), pp. 431-66.

\_\_\_\_\_. "Saving Babies: The Efficacy and Cost of Recent Changes in the Medicaid Eligibility of Pregnant Women." *Journal of Political Economy*, 1996b, 104(6), pp. 1263-96.

**Decker, Sandra.** "Disparities in Access to Health Care for Older Americans before and after Medicare," *International Longevity Center*. New York, NY, 2002.

**Decker, Sandra and Rapaport, Carol.** "Medicare and Disparities in Women's Health," National Bureau of Economic Research, Inc, NBER Working Papers: 8761, 2002.

**Dow, William H.** "The Introduction of Medicare: Effects on Elderly Health," University of California, Berkeley, 2004.

**Doyle, Joseph J, Jr.** "Health Insurance, Treatment and Outcomes: Using Auto Accidents as Health Shocks," National Bureau of Economic Research, Inc, NBER Working Papers, 2005.

**GAO.** "Hospital Emergency Departments: Crowded Conditions Vary among Hospitals and Communities," United States General Accounting Office, 2003.

**Kasper, J. D.; Giovannini, T. A. and Hoffman, C.** "Gaining and Losing Health Insurance: Strengthening the Evidence for Effects on Access to Care and Health Outcomes." *Med Care Res Rev*, 2000, 57(3), pp. 298-318; Discussion 19-25.

**Lee, David.** "Randomized Experiments from Non-Random Selection in U.S. House Elections." *Journal of Econometrics*, forthcoming 2005.

**Levy, Helen and Meltzer, David.** "What Do We Really Know About Whether Health Insurance Affects Health?" *Unpublished Working Paper, JCPR Working Paper 275*, 2001.

**Lichtenberg, Frank R.** "The Effects of Medicare on Health Care Utilization and Outcomes." *Frontiers in Health Policy Research*, 2001, 5(1), pp. 27-52 (26).

**Manning, W. G.; Newhouse, J. P.; Duan, N.; Keeler, E. B.; Leibowitz, A. and Marquis, M. S.** "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment." *The American Economic Review*, 1987, 77(3), pp. 251-77.

**McWilliams, J. M.; Zaslavsky, A. M.; Meara, E. and Ayanian, J. Z.** "Impact of Medicare Coverage on Basic Clinical Services for Previously Uninsured Adults." *Journal of the American Medical Association*, 2003, 290(6), pp. 757-64.

**National Foundation for Infectious Disease.** "US Surgeon General Joins Infectious Disease Experts to Urge Influenza, Pneumococcal Disease Vaccination," Press Release Dated October 7, 2002. Available at <http://www.nfid.org/pressconfs/flu02/release.html>.

Figure 1: Health Insurance Coverage By Age and Source, 1996-2004 CPS

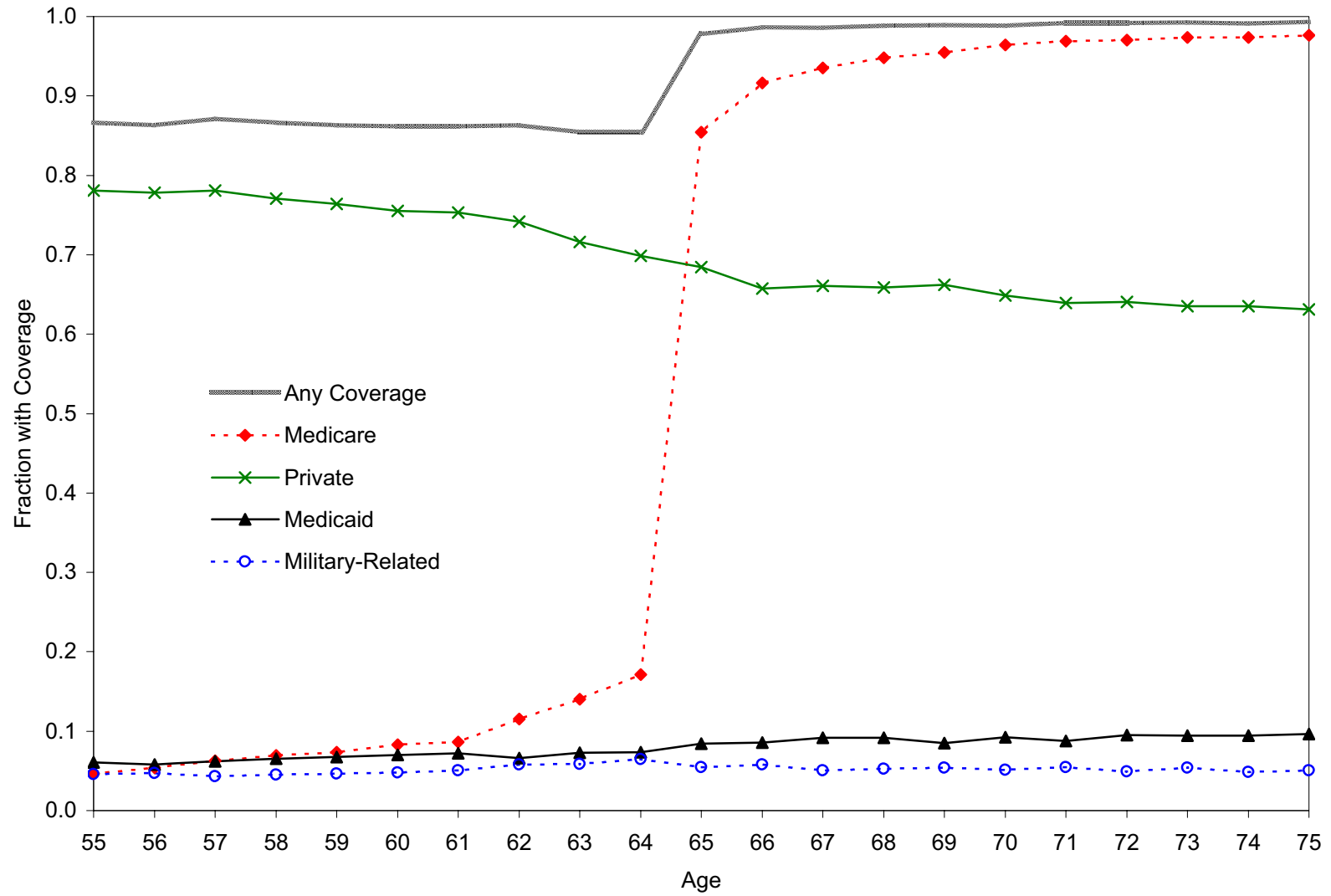
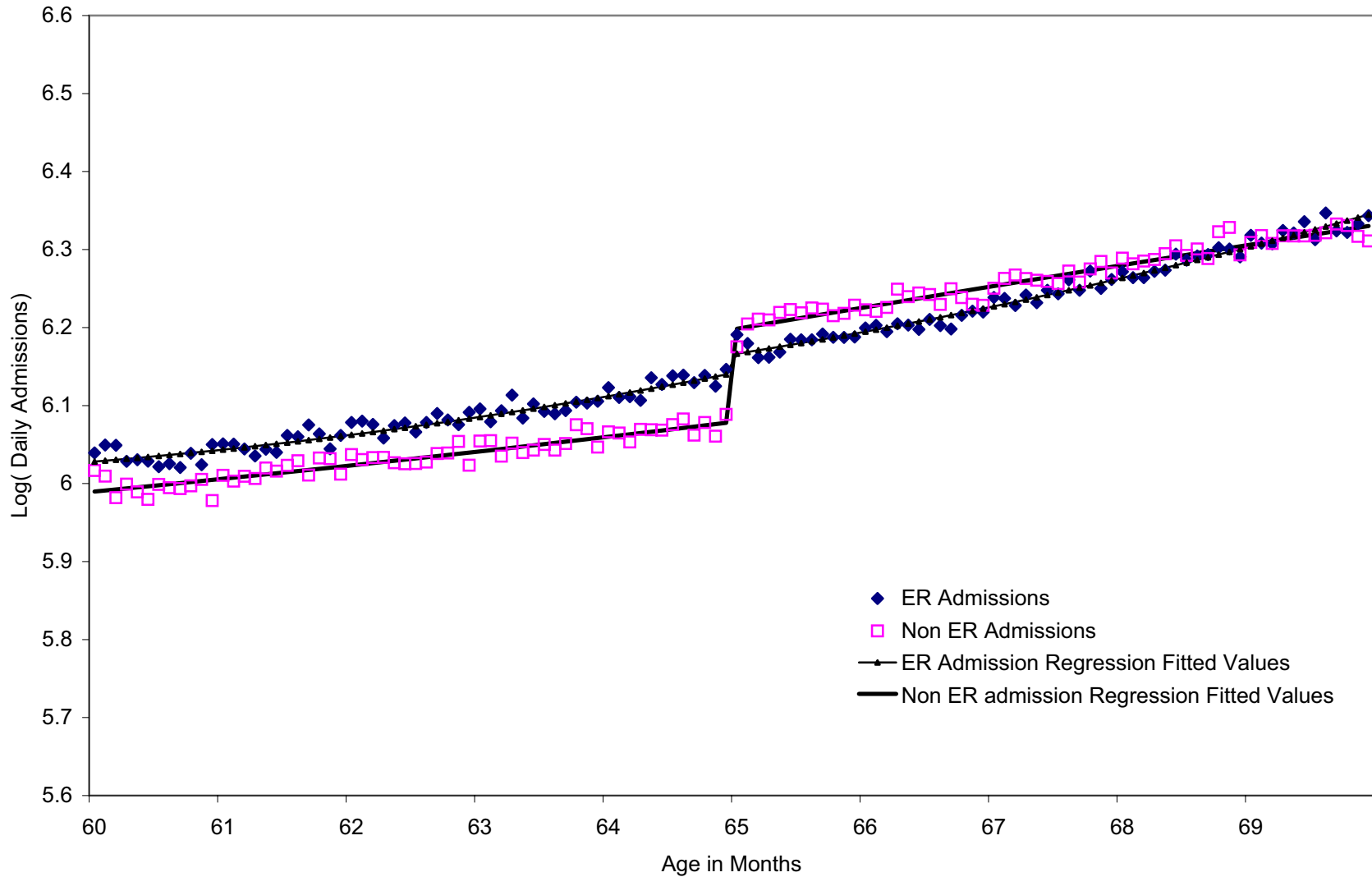
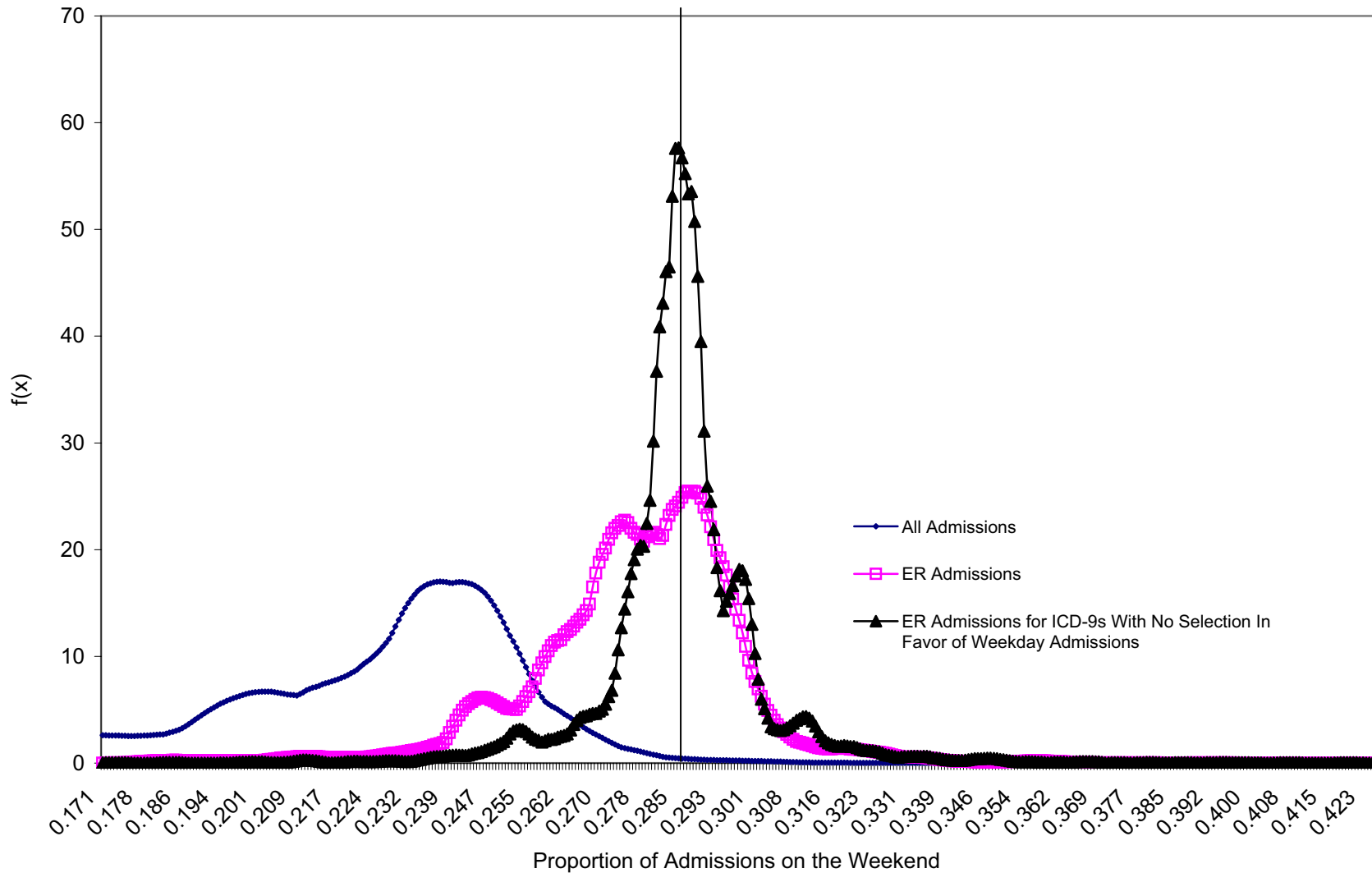


Figure 2: Hospital Admission by Route of Admission (California 1992-2002)



Notes: The points are the log of average daily admissions. The lines are the fitted values from regressions on day level counts that include a second order polynomial in age fully interacted with a dummy of age  $\geq 65$ .

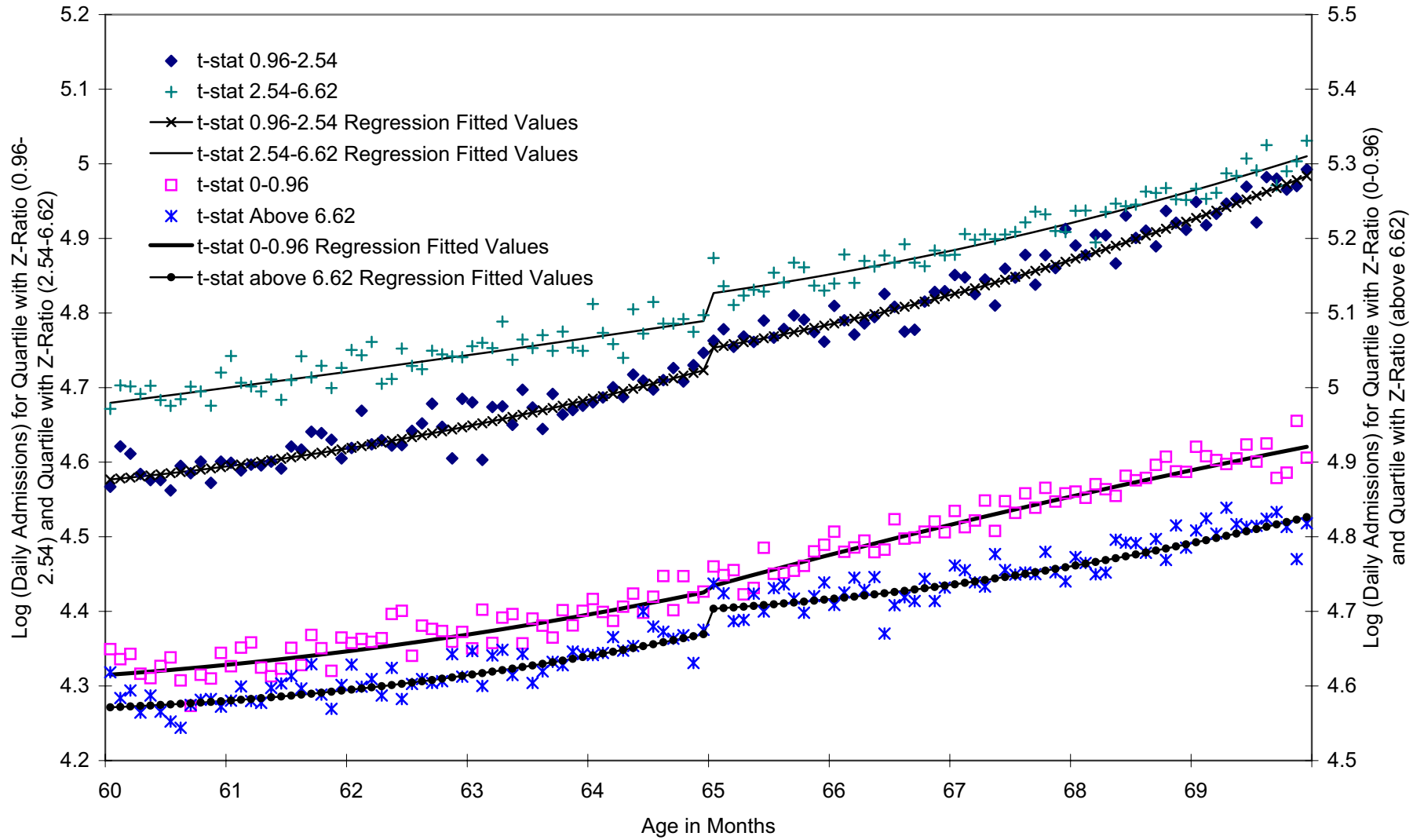
Figure 3: Proportion of Admissions that Occur on the Weekend by ICD-9



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.

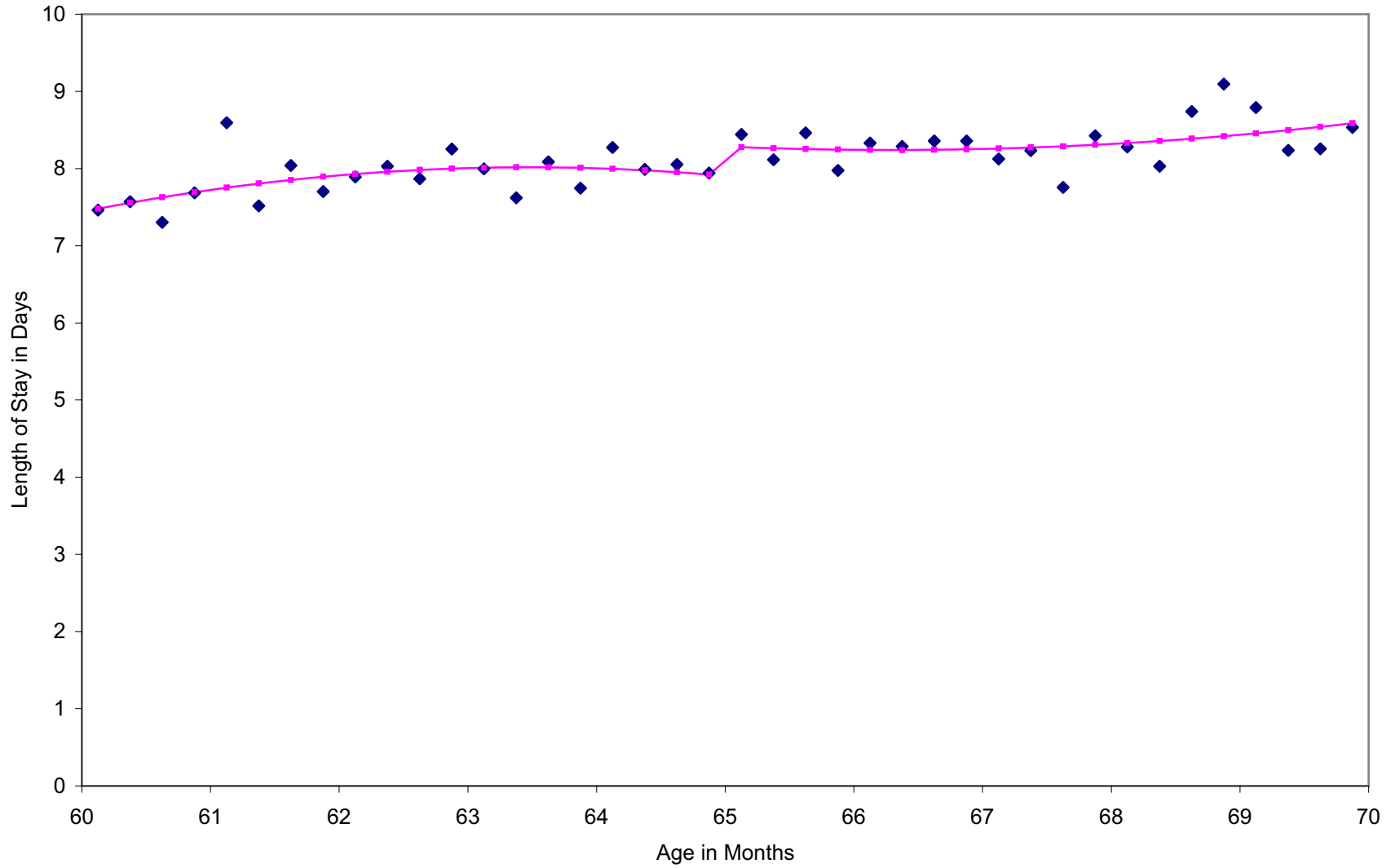


Figure 4: Admission Through the ER by Quartile of Weekend Proportion of ICD-9



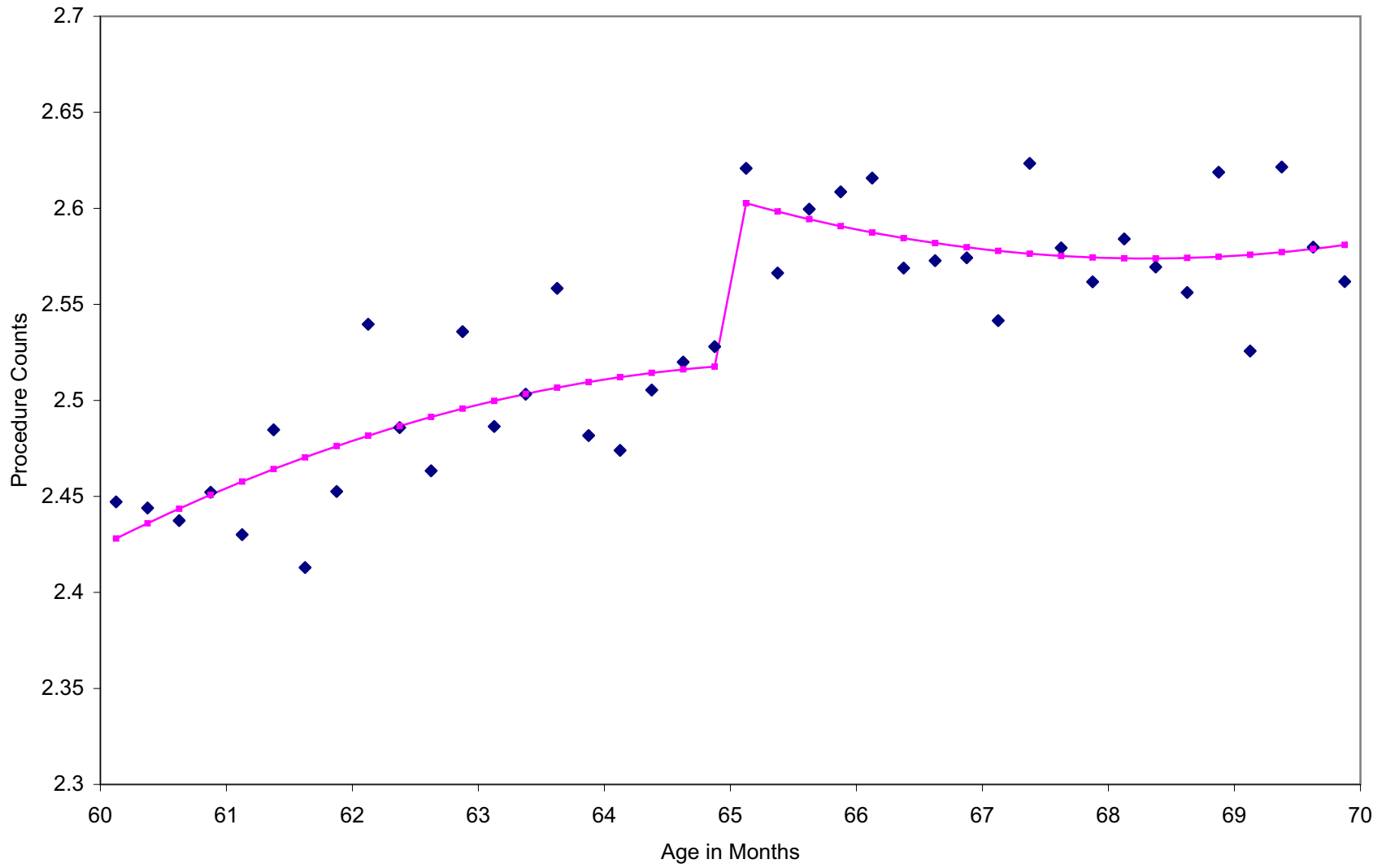
Notes: See notes from Figure 2. For the sample of ER admissions the age profiles above are created by computing the t-statistic for the test that an ICD-9 has a weekend to weekday ratio of 2:5. The admissions into quartiles based on the t-statistic.

Figure 5A: Length of Stay in Days



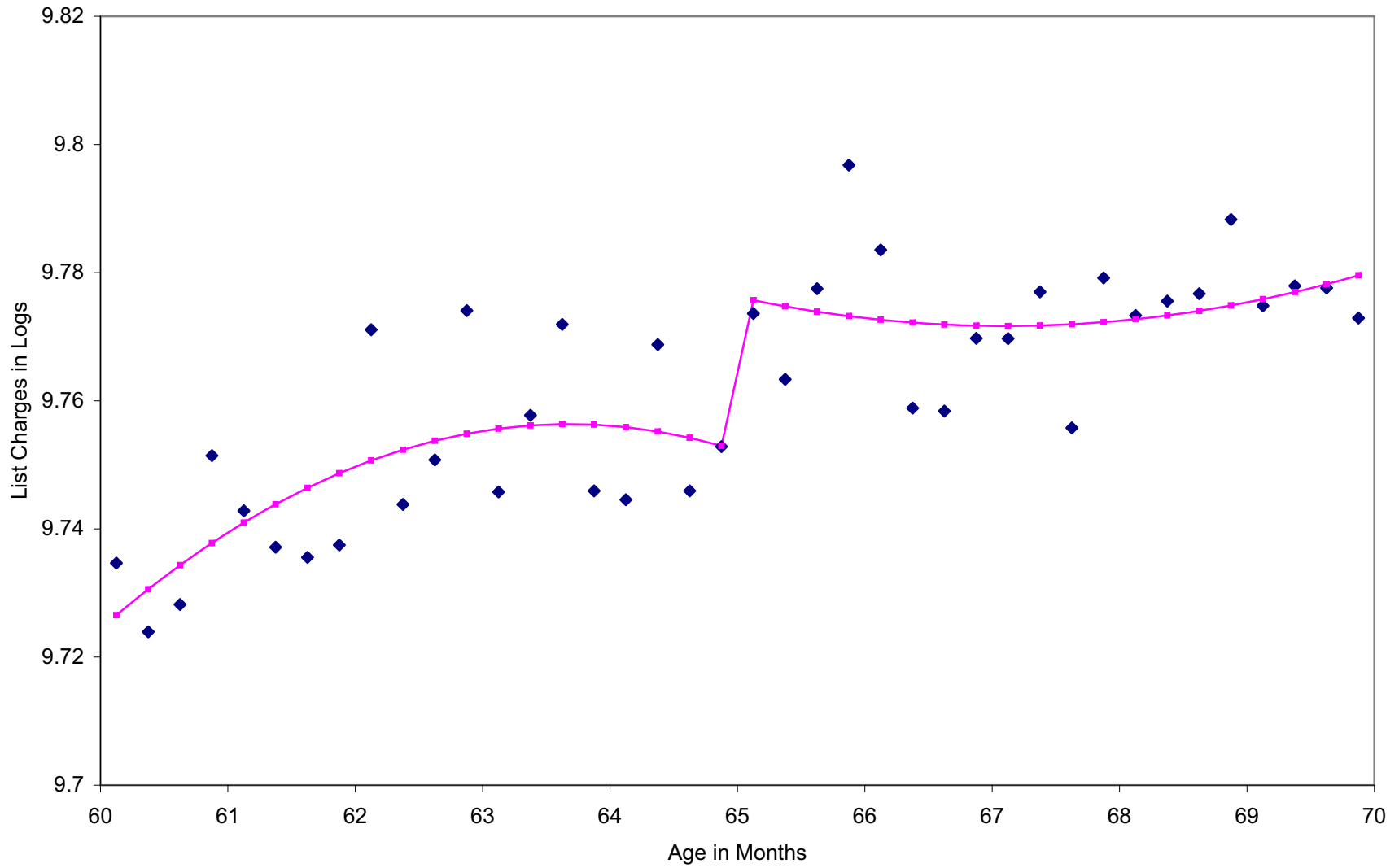
Notes: The points plotted in the figure are averages by age in quarters. The line is from a regression on the day level mean of length of stay. The regression includes a second order polynomial fully interacted with a dummy for age over 65.

Figure 5B: Counts of Procedures



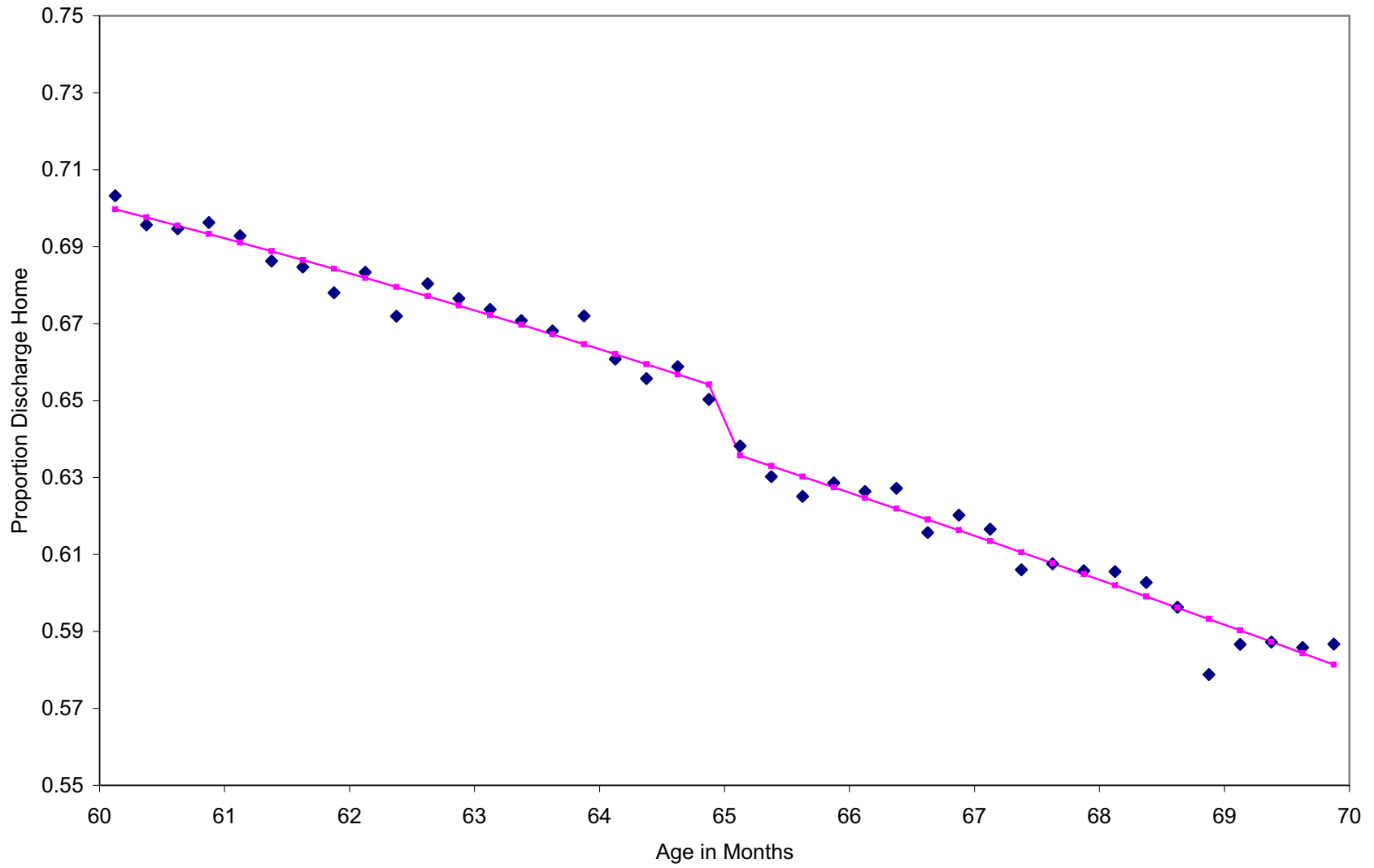
Notes: See the notes from Figure 5A.

Figure 5C: Hospital List Charges in Logs



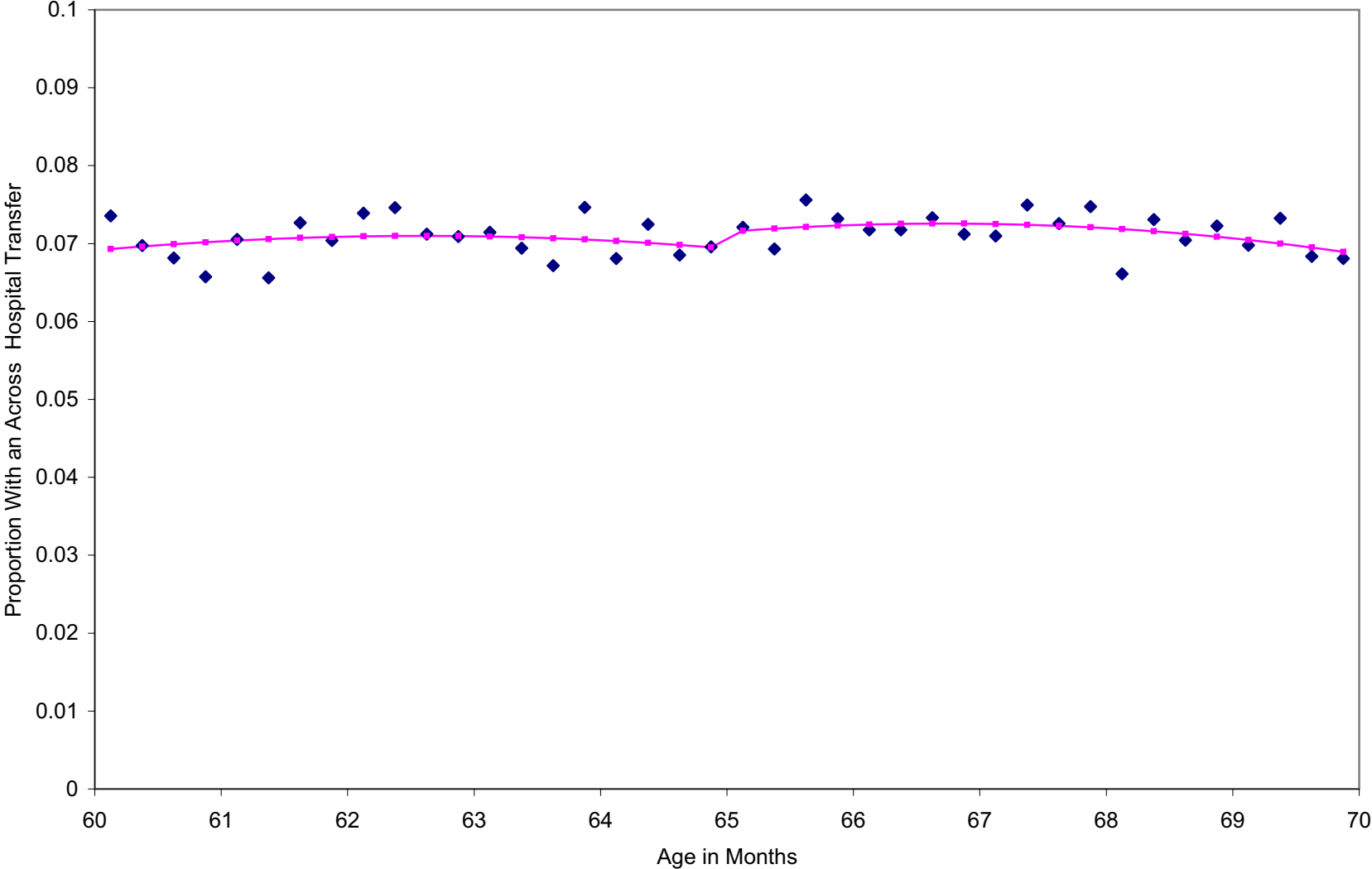
Notes: See the notes from Figure 5A.

Figure 6A: Proportion of Admissions Discharged to their Home



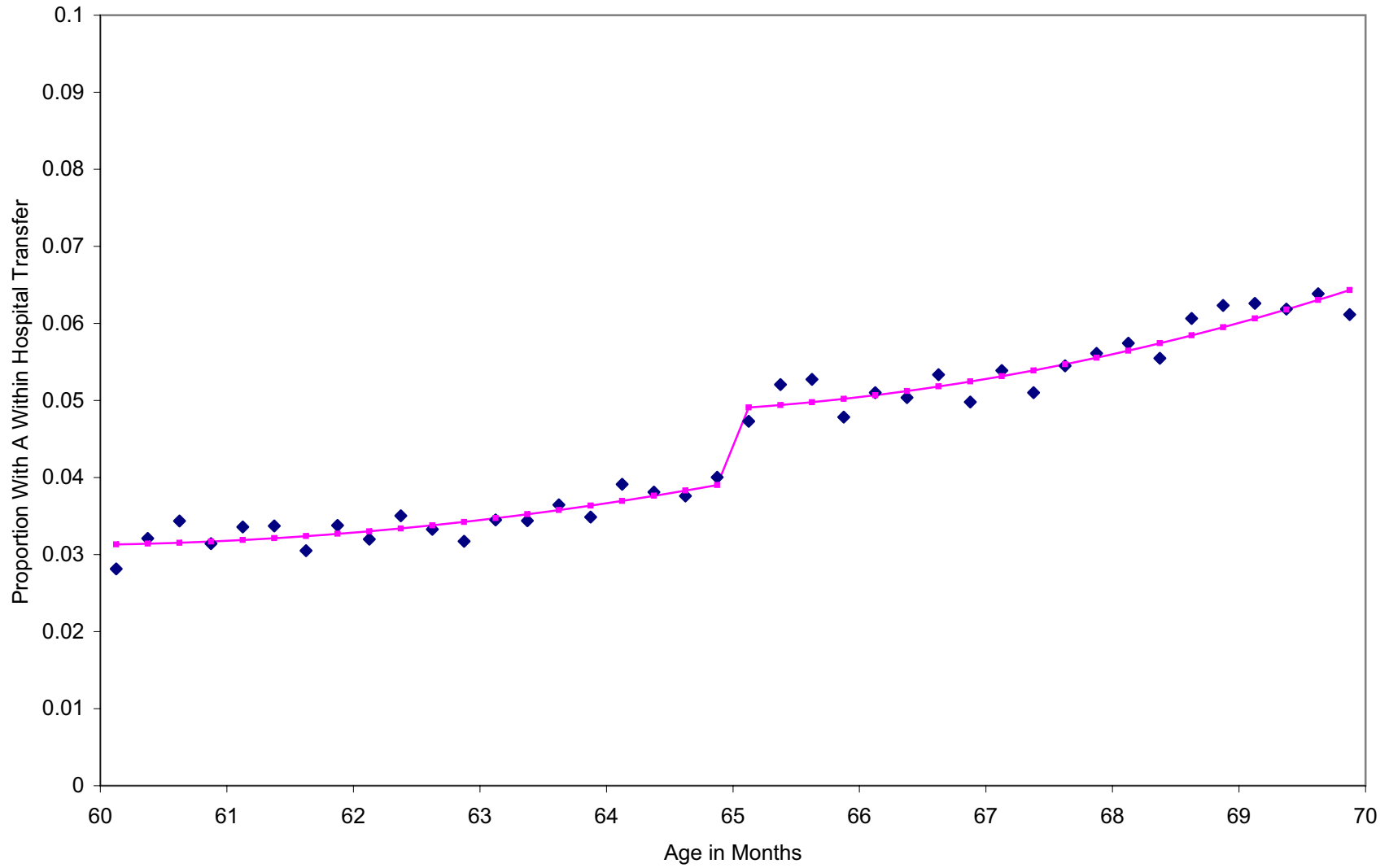
Notes: See the notes from Figure 5A.

Figure 6B: Proportion With an Across Hospital Transfer



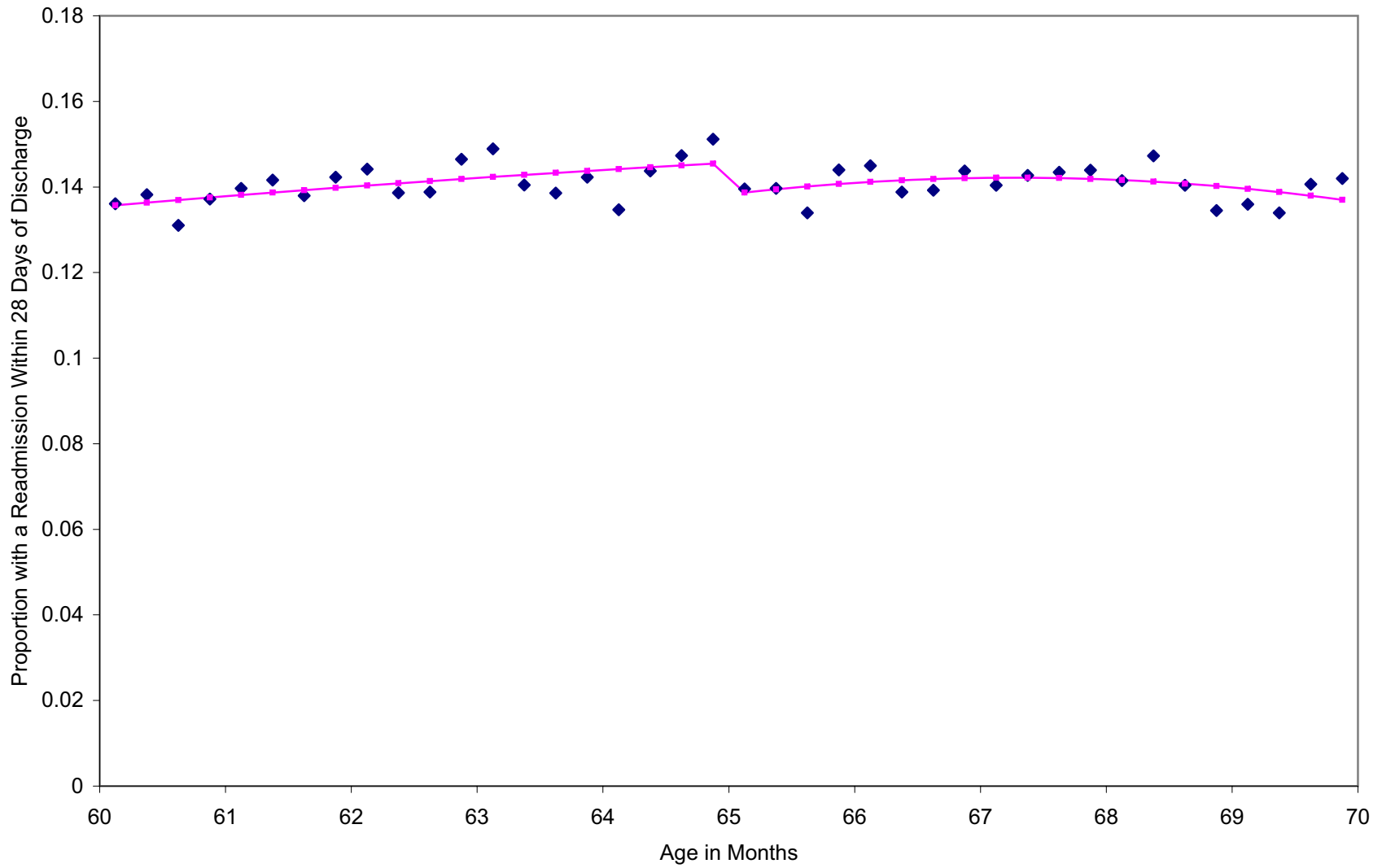
Notes: See notes from Figure 5A.

Figure 6C: Proportion of Patients with a Within Hospital Transfer



Notes: See notes from Figure 5A.

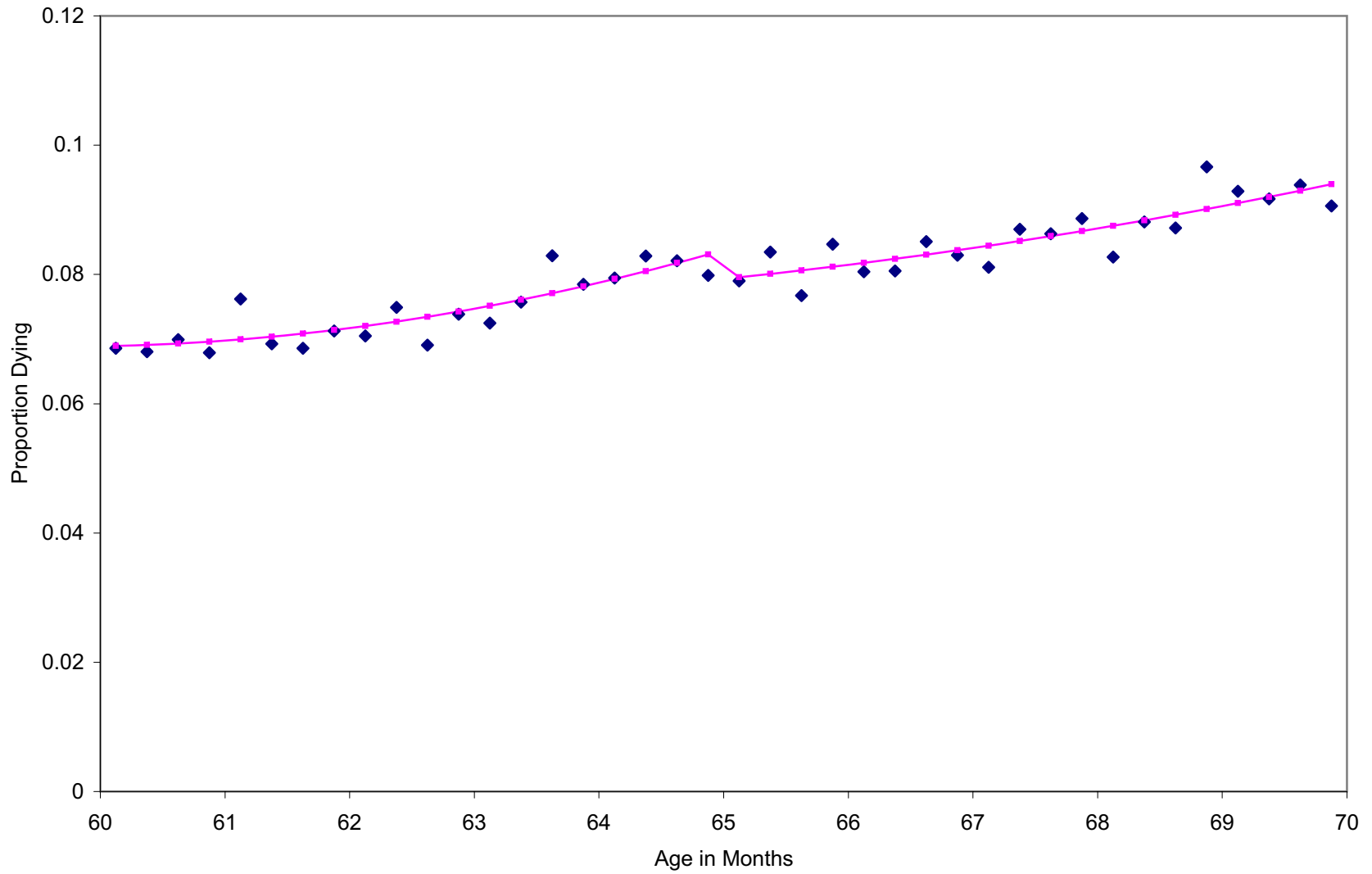
Figure 7: Readmission to Hospital Within 28 Days of Discharge



Notes: See notes from Figure 5A.



Figure 8: Proportion of Patients Dying Within the Hospital



Notes: See notes from Figure 5A.

Table 1: Characteristics of People Age 62-64 With and Without Health Insurance

	Overall Sample	Subsample With Insurance	Subsample Without Insurance	T-ratio
Have Health Insurance	90.1	100	0	--
Female	51.8	51.2	58.3	4.60
Married	72.6	74.2	58.0	10.65
Working	40.9	41.2	38.4	1.80
Poor (Family Income<Pov. Line)	7.1	5.8	19.3	11.37
White Non-Hispanic	81.1	83.1	62.6	13.94
Black Non-Hispanic	8.9	8.4	13.3	4.69
Hispanic	7.0	5.7	19.1	11.39
Other Race Non-Hispanic	3.0	2.8	5.0	3.30
High School Dropout	24.2	21.3	50.8	19.26
High School, No College	35.0	35.8	28.4	5.21
Some College	20.7	21.6	13.1	7.82
4 Years College or More	20.0	21.4	7.7	15.19
Daily Smoker	14.0	13.2	20.5	
Any Exercise in Past 30 Days	70.2	71.5	60.9	9.49
Overweight (BMI over 25.0)	67.6	67.4	69.2	1.19
Obese (BMI over 30)	25.1	24.7	28.0	2.13
In Good, Very Good, Excellent Health	79.4	79.9	74.1	4.2

Notes: Except as noted, means are based on data from pooled 1997-2001 NHIS. Percent with any exercise in past month, overweight, and obese are based on data from pooled 1998-2002 BRFSS.

Table 2: Estimates of Discontinuities at Age 65 in Employment, Marriage, Family Income, and Mobility

	Microdata from 1992- 2001 NHIS: Employed (1)	Cell-Level Data From 1996-2002 March CPS:					
		Employed (2)	Married Spouse Present (3)	Family Income <\$10,000 (4)	Family Income <\$15,000 (5)	Family Income <\$20,000 (6)	Moved to New House in Past Year (7)
All	-0.44 (0.96)	-1.27 (1.01)	-0.91 (0.70)	-0.42 (0.45)	-0.78 (0.63)	-0.10 (0.63)	-0.48 (0.33)
<u>By Ethnicity:</u>							
White Non-Hispanics	-0.67 (1.15)	-1.14 (0.98)	-1.00 (0.72)	-0.54 (0.37)	-0.67 (0.58)	-0.06 (0.61)	-0.53 (0.33)
Black Non-Hispanics	1.53 (2.05)	0.42 (1.90)	-1.25 (2.48)	1.60 (1.67)	-0.60 (1.77)	-1.07 (2.00)	0.12 (1.13)
Hispanics	0.36 (2.87)	-2.86 (2.10)	0.74 (2.63)	-1.85 (1.83)	-2.68 (2.43)	-1.58 (2.64)	1.57 (1.56)
<u>By Gender:</u>							
Men	1.12 (1.42)	-1.07 (1.74)	0.52 (1.13)	-1.37 (0.61)	-2.01 (0.76)	-1.19 (0.60)	-0.77 (0.55)
Women	-1.83 (1.14)	-1.65 (0.81)	-2.25 (0.83)	0.44 (0.70)	0.30 (1.00)	0.88 (0.90)	-0.22 (0.50)

Note: Table entries represent estimated coefficient of dummy for age 65 or older in models for outcome listed in column heading. Models in column (1) are fit to NHIS micro data; standard errors (in parentheses) are estimated assuming a cluster structure by age. Models in columns (2)-(7) are estimated using cell level data for ages 50-79 from March 1996-2002 CPS. Models include quadratic in age, fully interacted with a dummy for age 65 or older. Models in column (1) include year and region dummies.

Table 3: Changes in Admissions and Insurance at Age 65 for California Hospital Admissions 1992-2002

	<u>All Admissions</u>		<u>ER and Unplanned</u>		<u>Non ER or Planned</u>			
	<u>Admissions</u>	<u>Insurance</u>	<u>Admissions</u>	<u>Insurance</u>	<u>Admissions</u>	<u>Insurance</u>		
RD at 65	0.0713	-0.0554	0.0243	-0.0757	0.1187	-0.0332		
	0.0034	0.0007	0.0047	0.0012	0.0047	0.0008		
R-Squared	0.911	0.951	0.807	0.938	0.869	0.857		
Observations	3,651	3,651	3,651	3,651	3,651	3,651		
Underlying Obs	3,466,263	3,466,263	1,742,377	1,723,886	1,723,886	1,723,886		
	<u>Weekend t-stat &gt; 6.62</u>		<u>Weekend t-stat 2.54-6.62</u>		<u>Weekend t-stat 0.96-2.54</u>		<u>Weekend t-stat &lt; 0.96</u>	
	<u>Admissions</u>	<u>No Insurance</u>	<u>Admissions</u>	<u>No Insurance</u>	<u>Admissions</u>	<u>No Insurance</u>	<u>Admissions</u>	<u>No Insurance</u>
RD at 65	0.0322	-0.0729	0.0356	-0.0780	0.0271	-0.0739	0.0058	-0.0743
	0.0099	0.0022	0.0091	0.0022	0.0093	0.0023	0.0092	0.0022
R-Squared	0.388	0.797	0.533	0.810	0.630	0.805	0.520	0.808
Observations	3,651	3,651	3,651	3,651	3,651	3,651	3,651	3,651
Underlying Obs	397,276	397,276	456,745	456,745	425,522	425,522	424,643	424,643

Notes: These regressions are run on 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. The regressions include a second order polynomial in age fully interacted with a dummy for age greater than or equal to 65.

Table 4: Ten Most Common ICD-9s in the Group With Less Evidence of Selection

	<u>ICD-9</u>	<u>Admissions</u>	<u>Length of Stay</u>	<u>Procedures</u>	<u>List Charges</u>	<u>Died</u>	<u>Transfer Across Hospital</u>
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 5: Regression Discontinuity Estimates of Changes in Treatment Intensity

		<u>Length of Stay</u>		<u>Procedure Count</u>		
Age Over 65	0.37381 [0.23644]	0.37275 [0.23653]	0.36978 [0.23390]	0.08904 [0.03005]	0.08866 [0.02985]	0.09780 [0.02701]
Year /Month/Sat/Sun	N	Y	Y	N	Y	Y
Race and Gender	N	Y	Y	N	Y	Y
Condition FE	N	N	Y	N	N	Y
Mean Dep. Var.	7.964	7.964	7.964	2.507	2.507	2.507
Observations	424,643	424,643	424,643	424,643	424,643	424,643
R-squared	0.000	0.000	0.030	0.000	0.010	0.200
		<u>Log Charges</u>		<u>Log Charges Unavailable</u>		
Age Over 65	0.02464 [0.01078]	0.02489 [0.01060]	0.02633 [0.00910]	-0.00648 [0.00318]	-0.00660 [0.00317]	-0.00629 [0.00314]
Year /Month/Sat/Sun	N	Y	Y	N	Y	Y
Race and Gender	N	Y	Y	N	Y	Y
Condition FE	N	N	Y	N	N	Y
Mean Dep. Var.	9.754	9.754	9.754	0.138	0.138	0.138
Observations	367,571	367,571	367,571	424,643	424,643	424,643
R-squared	0.000	0.030	0.290	0.000	0.010	0.030

Notes: All the regressions are linear regression with robust standard errors. The regressions include a second order polynomial in age fully interacted with a dummy for age 65 or older. The inclusion of a third order polynomial has little impact on the estimates. The regressions include admissions that occur on or after Jan 1 1992 and before Dec 1, 2002.

Table 6: Regression Discontinuity Estimates of Transfer Probabilities

	<u>Discharged Home</u>			<u>Transferred</u>		
Age Over 65	-0.01525 [0.00444]	-0.01503 [0.00443]	-0.01681 [0.00401]	0.01633 [0.00357]	0.01625 [0.00356]	0.01709 [0.00334]
Year /Month/Sat/Sun	N	Y	Y	N	Y	Y
Race and Gender	N	Y	Y	N	Y	Y
Condition FE	N	N	Y	N	N	Y
Mean Dep. Var.	0.639	0.639	0.639	0.185	0.185	0.185
Observations	424,643	424,643	424,643	424,643	424,643	424,643
R-squared	0	0	0	0	0	0
	<u>Transferred to Another Hospital</u>			<u>Transferred Within Hospital</u>		
Age Over 65	0.00219 [0.00238]	0.00225 [0.00238]	0.00354 [0.00227]	0.00921 [0.00190]	0.00913 [0.00190]	0.00881 [0.00186]
Year /Month/Sat/Sun	N	Y	Y	N	Y	Y
Race and Gender	N	Y	Y	N	Y	Y
Condition FE	N	N	Y	N	N	Y
Mean Dep. Var.	0.071	0.071	0.071	0.046	0.046	0.046
Observations	424,643	424,643	424,643	424,643	424,643	424,643
R-squared	0	0	0	0	0	0

Notes: All the regressions are linear regression with robust standard errors. The regressions include a second order polynomial in age fully interacted with a dummy for age 65 or older. The inclusion of a third order polynomial has little impact on the estimates.

Table 7: Regression Discontinuity Estimates of Readmission Probabilities and Within Hospital Mortality

	<u>Readmission Within One Day</u>			<u>Readmission Within One Week</u>		
Age Over 65	-0.00151	-0.0015	-0.00141	-0.00301	-0.00301	-0.00295
	[0.00096]	[0.00096]	[0.00096]	[0.00213]	[0.00213]	[0.00212]
Year /Month/Sat/Sun	N	Y	Y	N	Y	Y
Race and Gender	N	Y	Y	N	Y	Y
Condition FE	N	N	Y	N	N	Y
Mean Dep. Var.	0.010	0.010	0.010	0.054	0.054	0.054
Observations	424,643	424,643	424,643	424,643	424,643	424,643
R-squared	0	0	0	0	0	0
	<u>Readmission within One Month</u>			<u>Died in Hospital</u>		
Age Over 65	-0.00747	-0.00753	-0.00777	-0.00426	-0.00422	-0.00285
	[0.00325]	[0.00325]	[0.00321]	[0.00252]	[0.00252]	[0.00232]
Year /Month/Sat/Sun	N	Y	Y	N	Y	Y
Race and Gender	N	Y	Y	N	Y	Y
Condition FE	N	N	Y	N	N	Y
Mean Dep. Var.	0.141	0.141	0.141	0.081	0.081	0.081
Observations	424,643	424,643	424,643	424,643	424,643	424,643
R-squared	0	0	0	0	0	0

Notes: All the regressions are linear regression with robust standard errors.