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ABSTRACT

Substantial uncertainty exists regarding the causal effect of health insurance on the utilization of care. Most studies cannot determine whether the large differences in healthcare utilization between the insured and the uninsured are due to insurance status or to other unobserved differences between the two groups. In this paper, we exploit a sharp change in insurance coverage rates that results from young adults "aging out" of their parents' insurance plans to estimate the effect of insurance coverage on the utilization of emergency department (ED) and inpatient services. Using the National Health Interview Survey (NHIS) and a census of emergency department records and hospital discharge records from seven states, we find that aging out results in an abrupt 5 to 8 percentage point reduction in the probability of having health insurance. We find that not having insurance leads to a 40 percent reduction in ED visits and a 61 percent reduction in inpatient hospital admissions. The drop in ED visits and inpatient admissions is due entirely to reductions in the care provided by privately owned hospitals, with particularly large reductions at for profit hospitals. The results imply that expanding health insurance coverage would result in a substantial increase in care provided to currently uninsured individuals.

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1. INTRODUCTION

Over one-quarter of nonelderly adults in the United States lacked health insurance during at some point in 2007 (Schoen et al. 2008). A large body of research documents a strong association between insurance status and particular patterns of health care utilization. The uninsured are less likely to consume preventative care such as diagnostic exams and routine checkups (Ayanian et al. 2000). They are more likely to be hospitalized for conditions that – if treated promptly – do not require hospitalization (Weissman et al. 1992). Such correlations suggest that when individuals lose health insurance, they alter their consumption of health care and their health suffers as a result.

But would the uninsured behave differently if they had health insurance? Individuals without health insurance have different discount rates, risk tolerances, and medical risks than those with health insurance, making causal inference difficult. Little evidence exists that overcomes this empirical challenge. Several studies leverage quasi-experimental variation to measure the impacts of Medicare and Medicaid, the two largest public insurance programs in the United States.[1] Such studies, however, provide little insight about the likely effects of coverage expansions on the current population of uninsured individuals for two reasons. First, they focus only on the near-elderly or the very young, both of whom are at low risk of being uninsured. Most of the uninsured are non-elderly adults, particularly young adults. Estimates of this population's reaction to changes in health insurance status are essential to evaluate public policies that would expand access to health insurance. Second, studies that focus on Medicare or Medicaid cannot separate the effects of gaining health insurance from the effects of a transition from private to public insurance.

In this paper, we overcome these challenges by exploiting quasi-experimental variation in insurance status that results from the rules insurers use to establish the eligibility of dependents. Many private health insurance contracts cover dependents "eighteen and under" and only cover older dependents who are full-time students. As a result, five to eight percent of teenagers become uninsured shortly after their nineteenth birthdays. We exploit this variation through a regression discontinuity (RD) design and compare the health care

[1] See, for instance, papers by Dafny and Gruber (2005), Card et al. (2008, 2009), and Currie et al. (2008).

consumption of teenagers who are just younger than nineteen to the health care consumption of those who are just older than nineteen.

We examine the impact of this sharp change in coverage using data from the National Health Interview Survey (NHIS); emergency department records from Arizona, California, Iowa, New Jersey, and Wisconsin; and hospital admission records from Arizona, California, Iowa, New York, Texas and Wisconsin. We find that the decrease in insurance coverage results in a decreased level of contact with health care providers. We estimate sizable reductions in emergency department (ED) visits, contradicting the conventional wisdom that the uninsured are more likely to visit the ED. We also find substantial reductions in non-urgent hospital admissions. The decrease in both ED and inpatient visits is driven in large part by a drop in visits for less-severe medical conditions. Overall, these results suggest that an expansion in health insurance coverage would substantially increase the amount of care that currently uninsured individuals receive and require an increase in net expenditures.

The paper proceeds as follows. The following section describes previous research on insurance and utilization. Section 3 outlines our econometric framework. We document the change in insurance coverage in Section 4. Sections 5 and 6 present results for ED visits and inpatient hospitalizations respectively. In Section 7 we discuss the potential generalizability of our results. Section 8 concludes.

2. PRIOR EVIDENCE ON THE HEALTH CARE CONSUMPTION OF THE UNINSURED

The uninsured tend to consume expensive health care treatments when cheaper options are available. Weissman et al. (1992) find that the uninsured are much more likely to be admitted to the hospital for a medical condition that could have been prevented with timely care. Similarly, Braveman et al. (1994) estimate that the uninsured are more likely to suffer a ruptured appendix, an outcome that can be avoided with timely care. Dozens of similar studies are summarized in an Institute of Medicine (2002) report, and nearly all find a robust correlation between a lack of insurance and reliance on expensive, avoidable medical treatments. Some evidence also suggests that the uninsured are more likely to seek care in the ED than the insured (Kwack et al. 2004), and it is commonly assumed that uninsured patients visit the ED for non-urgent problems and contribute to ED crowding (Abelson 2008, Newton et al. 2008).[2]

Given the substantial underlying differences between the insured and the uninsured, the correlations documented in these studies may not represent causal effects. To our knowledge, only two sets of studies have used credible research designs to determine the causal effect of insurance status on health care utilization. The first of these evaluates Medicaid expansions. Dafny and Gruber (2005) estimate that Medicaid expansions led to an increase in total inpatient hospitalizations, but not to a significant increase in avoidable hospitalizations. The authors conclude that being insured through Medicaid leads individuals to visit the hospital more often and, potentially, to consume health care more efficiently.

Other papers study the effect of Medicare on health care utilization. Finkelstein (2007) studies the aggregate spending effects of the introduction of Medicare, and Card et al. (2008, 2009) study the effects of Medicare on individual health care consumption. All three papers conclude that Medicare leads to a substantial increase in health care consumption.

One limitation of such studies is that individuals who gain health insurance through Medicaid and Medicare are often insured beforehand. Cutler and Gruber (1996) demonstrate that fifty percent of new Medicaid enrollees were previously enrolled in employer-provided insurance plans. Similarly, Card et al. (2008) conclude that much of the increase in hospitalizations that occurs after people become eligible for Medicare is likely due to transitions from private insurance to Medicare rather than from no insurance to Medicare. Consequently, these papers do not isolate the causal effect of being uninsured on health care consumption, which is the object of interest here.

The other limitation of studies focused on Medicare and Medicaid is that their estimates are based on the demographic groups at lowest risk of being uninsured. Precisely as a result of these two programs, only a small fraction of children or the elderly lack health insurance. Most of the uninsured are non-elderly adults, and over half of uninsured non-elderly adults

[2] In spite of the positive cross-sectional correlation between uninsured status and ED utilization, however, Kwack et al. (2004) find no significant effect of the implementation of a managed care program on ED use patterns for formerly uninsured patients.

are between the ages of 19 and 35 (Kriss et al. 2008). Estimates of the effects of health insurance coverage on the near-elderly and children are unlikely to be very informative about the effects of insurance coverage expansions, as such expansions will disproportionately affect young adults.

This study contributes to the literature on health insurance in several respects. First, it isolates the effects of uninsured status, avoiding contamination by transitions from private to public insurance. Second, it focuses on young adults, a group that is more representative of the uninsured population than either children or the elderly. Third, it introduces a corrected instrumental variables estimator for data based on a self-selected population, in this case, those who present at the hospital.

3. Empirical Framework

Consider a reduced-form model of the effects of health insurance coverage on health care utilization:

(1)
$$Y_i = \gamma_0 + \gamma_1 D_i + \varepsilon_i$$

In this model, Y_i represents the utilization of care of individual i, and D_i is an indicator variable equal to unity if individual i has health insurance. The error term, ε_i, corresponds to all other determinants of the outcome Y_i. The coefficient γ_1 represents the causal effect of health insurance on utilization.

It is difficult to obtain consistent estimates of γ_1 because health insurance status, D_i, is correlated with unobserved determinants of utilization. An individual chooses to acquire health insurance based on her health and other characteristics that affect both the choice to be insured and health outcomes. Some of these characteristics are observable to researchers but many are not; uninsured individuals likely have different discount factors, risk tolerances, and medical risks than those with health insurance. In the first two columns of Table 1 we present summary statistics by health insurance status for young adults (age 18–19) from the NHIS. Insured individuals are less likely to be minorities, less likely to be male, less likely to smoke, and more likely to be attending school. Since observable characteristics are correlated with insurance status, it is likely that unobservable characteristics are also correlated with insurance status. Consequently, we rely on an instrumental variables strategy, and identify the causal effect of health insurance via the sharp discontinuity in insurance coverage rates at age 19.

Let $Z_i = 1\{A_i > 19\}$ be an indicator variable equal to unity if individual i is older than 19.[3] When young adults turn 19, they become less likely to be insured. We assume, however, that no other variables in equation (1) are affected. In particular, we assume that $E[\varepsilon_i \mid A_i = a]$ is continuous at $a = 19$. This assumption would be violated if other factors affecting health care such as employment, school attendance, or risky behaviors, change discontinuously when young adults turn 19. We discuss this assumption below and present empirical evidence that it holds in the fifth and sixth columns of Table 1.

Since age is not the sole determinant of insurance coverage, the RD design that we implement is a "fuzzy" RD (Campbell 1969). We estimate the reduced form effect of age 19 on each outcome of interest Y_i:

(2) $$Y_i = \alpha_0 + \alpha_1 Z_i + \alpha_2 (A_i - 19) + \alpha_3 Z_i (A_i - 19) + v_i$$

We estimate the first stage – the share of young adults who lose insurance coverage at age 19 – in two ways. First, we estimate a straightforward version of equation (2) in the NHIS with insurance coverage on the left-hand side. Second, we estimate the first stage using hospital records. This poses an additional econometric challenge, however, as the records contain a census of visits rather than individuals. In Section 5 we describe the problem and develop a method for consistently estimating the first stage using the hospital records.

[3] Many private health plans cover dependents through the last day of the month in which the dependent turns 19 (Kriss et al 2008). In Appendix 1 we present empirical evidence that this is the case for the majority of plans in California. In the regressions that follow, we code Z_i accordingly. The abrupt decrease in private coverage documented in Figures 5 and 8 is further evidence that this coding is correct. However, to simplify the discussion we describe people as aging out when they turn 19.

We can identify γ_1, the causal effect of health insurance coverage (D_i) on outcome Y_i, by combining the first stage and reduced form results. We identify this parameter by dividing the effect of turning 19 on outcome Y_i by the effect of turning 19 on health insurance coverage, D_i. This strategy is analogous to using the age 19 discontinuity as an instrument to identify the causal effect of health insurance (Hahn et al., 2001).

4. The Change in Insurance Coverage Rates at 19, Results from the NHIS

Figure 1 plots the age profile of insurance coverage, ED visits, and inpatient hospital stays. The solid line plots the share uninsured by age. It demonstrates a sharp increase at age 19, one that is larger than the *decrease* in share uninsured at age 65 (due to Medicare). The figure reveals that young adults are the age group most likely to be uninsured and that the probability of being uninsured peaks around age 22.

Figure 1 also suggests that young adults are not atypical in their consumption of inpatient and ED visits when compared to the majority of the adult population. Young adults near age 19 have a similar probability of having had at least one inpatient visit in the prior year – roughly 9% – as adults through age 55. The probability of an ED visit is somewhat higher for young adults than middle-aged adults, suggesting that young adults may be more representative of the typical ED visitor.

We explore the change in insurance coverage rates more closely by restricting the NHIS sample to those within one year of their nineteenth birthday. The NHIS includes questions on the type of insurance coverage that a respondent has and whether the respondent has lost coverage due to age or leaving school. We combine NHIS data from 1997 to 2007 and keep only respondents between 18 and 20 years of age. This trimmed sample includes 24,260 observations. Figure 2 plots the age profiles of four insurance coverage types: private insurance, uninsured, Medicaid, and other insurance. Immediately at age 19, there is a four-percentage-point increase in the share of NHIS respondents who report being uninsured.

The figure makes clear that the increase is driven primarily by a decrease in those covered by private insurance, and less so by respondents losing Medicaid and other forms of insurance.[4]

The abrupt drop in coverage rates is due in large part to a decline in insurance coverage rates among people not enrolled in school. In Figure 3 we present the proportion uninsured by age for NHIS respondents that are not attending school and for NHIS respondents that are attending school.[5] The age profiles in the figure reveal a much larger loss of coverage among the group that is not in school than for the general population.[6] Though the proportion of the total population that is uninsured increases by only 4.1 percentage points (Figure 2), the proportion of out of school respondents who are uninsured increases by 7.1 percentage points (Figure 3). This difference is due to the mechanism behind the change in coverage rates; many private insurance plans cover dependents beyond age 18 only if the dependents are enrolled in school.

Figure 4 provides further evidence that the abrupt decline in insurance coverage at age 19 is due to people aging out of their parents' plans. The NHIS asks respondents why they do not have health insurance. Figure 4 plots, by age, the share of respondents who report having lost coverage due to age or leaving school.[7] For individuals who are not in school, the proportion who report losing insurance for this reason jumps by 5.6 percentage points at age 19. This increase accounts for almost all of the 7.1 percentage point increase in the proportion uninsured for this group. In contrast, the proportion of people who are still in school that lose coverage due to age or leaving school increases by only 0.5 percentage points at age 19.

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4 "Other forms of insurance" include Medicare (for disabled individuals), State Children's Health Insurance Program (SCHIP), military health care (e.g., Veterans Affairs health care), and other public, non-Medicaid/Medicare health care (e.g., Indian Health Service).

5 NHIS respondents are asked if they have a job or are looking for work. Those that respond negatively can choose among several explanations, one of which is "Going to School." We coded people who responded "Going to School" as in school, though the pattern of questions makes it likely that some individuals that are in school but are working will be coded as not in school.

6 Note that the group sizes change with age. The number of individuals in school trends downward with age, while the number of individuals not in school trends upwards with age. However, as can be seen in Table 1, there is no evidence of discrete changes in the group sizes at the age 19 threshold.

7 In the National Health Interview Survey the respondent is asked the following question regarding all household members that are currently without health insurance: "Which of these are reasons (you/subject name) stopped being covered or do not have health insurance?" One possible answer they can choose from is, "Ineligible because of age/left school".

In Table 2 we present estimates of the discrete change in insurance coverage at age 19 for the overall population and for the two subgroups examined in Figure 3. We estimate the size of the discrete change in coverage by estimating equation (2) using the individual-level NHIS data, restricting our sample to people surveyed within 12 months of the month in which their 19th birthday falls.[8] Each coefficient represents the effect of turning 19 on a specified outcome (we report only $\hat{\alpha}_1$, the coefficient on the age 19 indicator, $Z_i = 1\{A_i > 19\}$). Each main row in Table 2 presents results for a different demographic group (all respondents, not attending school, attending school), and each main column presents results for a different outcome (privately insured, uninsured, Medicaid, and other insurance).[9] Within each main column, the left sub-column reports results for the specification described in equation (2), and the right sub-column reports results for a modified specification that also includes indicator variables for marital status, employment status, race and gender. The additional covariates slightly increase precision but generally do not affect the point estimates, providing further evidence that demographic covariates do not change discontinuously at the threshold.[10]

In the first two columns of Table 3 we present the regression estimates corresponding to Figure 4. Overall, there is a 4.3 percentage point increase in NHIS respondents who report losing insurance at age 19 due to age or leaving school. The NHIS also classifies insurance status by whether the respondent is insured in his or her own name or is covered by another person's plan. The third and fourth columns demonstrate that there is no discrete increase in the proportion of individuals with coverage in their own name, suggesting that people are not replacing their parents' insurance with their own insurance.[11]

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[8] We use a uniform kernel and a bandwidth of 365 days. The regressions are estimated via a procedure that takes into account the stratified sampling frame and the deliberate oversample of minorities in the NHIS. In Appendices 2–4 we present evidence that the regression results are fairly robust to the bandwidth choice. When estimating the change in insurance coverage using hospital records datasets, we find that the results are insensitive to bandwidth choice.

[9] The full age profiles by level of education that correspond to the second and third rows of the table are presented in Appendices 5 and 6.

[10] The third row of Table 2 suggests that respondents in school are gaining private insurance at age 19. However the estimates are only marginally significant at conventional levels. Furthermore, we find that estimates for this group are sensitive to the inclusion of covariates, unlike the estimates in the first and second rows of the table.

[11] The age profiles corresponding to the regression results are presented in Appendix 7.

In sum, we find a large, sudden increase in the share uninsured at age 19 in the NHIS data. This increase is driven largely by the individuals that are not in school and thus are at risk of aging out of their parents' insurance plans. In the following sections, we exploit this discontinuity in insurance status to determine how insurance status affects the consumption of health care services.[12]

5. THE EFFECTS OF HEALTH INSURANCE ON EMERGENCY DEPARTMENT VISITS

Many young adults receive health care at hospital emergency departments. From 2005 to 2007, approximately 26 percent of 18 and 19 year old NHIS respondents reported receiving treatment in an emergency department in the prior 12 months. ED utilization is of substantial policy interest for two reasons. First, ED crowding is a serious public health issue (Fatovich 2002; Trzeciak and Rivers 2003; Kellermann 2006). Whether insurance coverage expansions will alleviate or exacerbate ED crowding depends on how insurance coverage affects ED utilization. Second, the ED is an expensive location to receive care. Bamezai et al. (2005) estimate that the marginal cost of a non-trauma ED visit is $300, a number that exceeds the average price, let alone the marginal cost, of a doctor's visit.[13,14] Whether insurance coverage increases or decreases net ED usage thus affects the net cost of insurance coverage expansions.

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12 We find evidence in the NHIS that at age 19 there is an increase in the proportion of respondents that forgo or delay care due to cost in the last 12 months and no discernable change in the proportion of respondents that have seen a health care professional in the last two weeks. However, we do not present these results in the body of the paper because the first two results are substantially biased downward due the retrospective nature of the questions and the third result is imprecise due to the modest sample size. These results are presented in Appendices 8-10, where the bandwidth has been increased to 1.75 years so as to reduce the amount of attenuation bias and increase the precision of the estimates.

13 The average total payment for a doctor visit recorded in the Medical Expenditure Panel Survey is $120.

14 A minority view, put forward by Williams (1996), posits that the marginal cost of an ED visit is relatively low, and that EDs charge high prices to transfer the costs of uncompensated care onto the insured. Market-based tests suggest, however, that ED visits are indeed more expensive than visits to a private doctor. Health maintenance organizations (HMOs) generally enjoy bargaining power over hospitals but still reimburse hospitals hundreds of dollars for each ED visit (Polsky and Nicholson 2004). Additionally, some HMOs own hospitals and therefore absorb the true marginal cost of an ED visit when their customers visit EDs. Were ED visits less costly than doctor visits, one would expect such HMOs to shift their customers into the ED. But these HMOs still provide incentives for patients to use doctor offices rather than EDs. A representative plan for the individual market from HMO Kaiser Permanente, for example, charges a $150 copayment for an ED visit but a $50 copayment for a doctor visit.

The questions regarding ED visits in the NHIS ask about visits in the last year. This, combined with the modest sample size, make it impossible to generate precise estimates of how much the probability of an ED visit changes when a person loses their health insurance coverage. As an alternative we examine a near census of emergency department visits from Arizona, California, Iowa, New Jersey, and Wisconsin.[15] The records for Arizona and California span the 2005 to 2007 calendar years, the records for Iowa and New Jersey span the 2004 to 2007 calendar years, and the records for Wisconsin span the 2004 to 2006 calendar years. For the age group that is the focus of our analysis, 18 and 19 year olds, we observe 1,744,394 emergency department visits. For each visit, we observe basic demographic information including race, ethnicity, gender, type of health insurance, and age in months. In addition the dataset includes detailed information on the cause of the visit to the ED and the treatment received.

Figure 5 presents the age profile of insurance status for visitors to the emergency department.[16] Specifically, we plot the proportion with each type of insurance coverage for non-overlapping cells of one month of age and superimpose the fitted values from equation (2). For most of the states in our sample we are only able to compute age in months as the exact date of treatment is not available due to confidentiality concerns. However, this does not result in any attenuation bias as the indicator variable Z_i is measured without error.[17] The figure reveals that the proportion of individuals with private coverage drops steadily with age, while the proportion that is uninsured increases with age. Though the age profile of insurance coverage has a similar shape to the general population estimates from the NHIS in Figure 2, some of the levels are notably different. Estimates from the emergency department data show lower rates of private coverage and higher rates of Medicaid and lack of insurance coverage. Estimates from the NHIS of the insurance coverage of young adults that have received treatment in the emergency department in the prior year show a distribution of

[15] Emergency Department visits at hospitals that are not under state oversight such as Veteran Affairs hospitals are not included in these datasets.
[16] The expected payer is reported on the medical records.
[17] In all the datasets we observe both the month of birth and the month in which treatment is received. Since people age out of their parents insurance at the end of the month in which their birthday falls, we can correctly code the instrument Z_i using only these two variables. In addition, the coarse age variable does not substantially bias or reduce the precision of our estimates, as can be seen in Appendix 11.

health care coverage that is reasonably close to the distribution found in the emergency department data.[18]

Figure 5 also reveals that there is a discrete reduction in private insurance coverage immediately after teenagers turn 19 and a corresponding increase in the proportion uninsured. The proportion privately insured decreases by 5.0 percentage points, and the proportion uninsured increases by 5.7 percentage points.[19] Regression estimates of this change, however, understate the true size of the reduction in the percentage insured. This attenuation bias stems from the decrease in visits (apparent in the analysis below) that occurs as the newly uninsured become less likely to visit the ED.

The estimates in Figure 5 come from the sample analog of the following equation:

$$\pi_1 = \lim_{a \downarrow 19} \mathrm{E}\left[D_i \middle| A_i = a\right] - \lim_{a \uparrow 19} \mathrm{E}\left[D_i \middle| A_i = a\right] \tag{3}$$

where D_i is an insurance coverage indicator and A_i is age. The quantity π_1 represents the discrete change in the proportion insured that occurs at age 19 among people visiting the emergency department. However, π_1 is a biased estimate of the true reduction in insurance coverage because $\lim_{a \downarrow 19} \mathrm{E}\left[D_i \middle| A_i = a\right]$ is estimated from a population that is more likely to be uninsured and thus less likely to visit the ED. The population of ED visitors post-19 is therefore not comparable to the population of ED visitors pre-19.[20]

Under standard RD assumptions we can adjust our estimates of the first stage to estimate population-level parameters of interest. Suppose that $D_i(1)$ and $Y_i(1)$ indicate whether an individual is insured and whether they visit the ED, respectively, when they are older than

[18] The proportion with private, Medicaid and no coverage in the ED data are (0.42, 0.25, 0.25). In the general population estimates from the NHIS, they are (0.62, 0.10, 0.20). In the NHIS estimates restricted to people with a visit to the emergency department in the past year, they are (0.53, 0.19, 0.18).

[19] These estimates are robust to choice of bandwidth, as can be seen in Appendix 12.

[20] These issues would not affect our estimates if we had population-level estimates of the first-stage equation. The sample size of the NHIS, however, is too small to generate a precise estimate of the first-stage effect of age 19 on insurance coverage when restricted to the states for which we have ED visit data.

19. The indicator functions $D_i(0)$ and $Y_i(0)$ are defined similarly for individuals younger than 19. We would like to estimate:

(4) $$\mathrm{E}\left[D_i(1) \mid Y_i(0)=1\right] - \mathrm{E}\left[D_i(0) \mid Y_i(0)=1\right].$$

That is, we wish to measure the change in the probability of being insured at age 19 conditional on visiting the ED before age 19. Instead, what we observe in the data is:

(5) $$\mathrm{E}\left[D_i(1) \mid Y_i(1)=1\right] - \mathrm{E}\left[D_i(0) \mid Y_i(0)=1\right].$$

We observe the share insured, but for two distinct populations: those who visit the ED after they turn 19 and those who visit the ED before they turn 19. These two populations are not directly comparable because, as we document below, insurance coverage affects the probability that a person receives treatment in the ED. We correct for the bias in our first-stage estimates under the assumption that the net change in observed ED visits at age 19 is driven only by individuals who lose insurance coverage. This assumption is implied by the standard IV exclusion restriction.

We adopt the following notation for counts of visits and insured patients: y_0 indicates visits made before age 19, d_0 indicates number of insured patients younger than 19, and y_1 and d_1 are defined similarly for patients older than age 19. The ratios $\frac{d_0}{y_0}$ and $\frac{d_1}{y_1}$ thus represent the fraction of insured ED patients before and after 19 respectively. We show in Appendix A that the following bias-corrected estimator converges to the quantity of interest:

(6) $$\frac{d_1}{y_1 + (y_0 - y_1)} - \frac{d_0}{y_0} = \frac{d_1 - d_0}{y_0} \xrightarrow{p} \mathrm{E}\left[D_i(1) - D_i(0) \mid Y_i(0)=1\right].$$

Intuitively, the term $(y_0 - y_1)$ "adds back in" the individuals who stop visiting the ED because they lose insurance coverage. We thus consistently estimate the average change in insurance coverage for individuals who visit the ED prior to turning 19. Translating equation (6) into RD quantities yields a bias-corrected first-stage equation of:

(7) $$\frac{\lim\limits_{a\downarrow 19} \mathrm{E}\left[D_i \middle| A_i = a\right] \cdot \lim\limits_{a\downarrow 19} \mathrm{E}\left[Y_i \middle| A_i = a\right]}{\lim\limits_{a\uparrow 19} \mathrm{E}\left[Y_i \middle| A_i = a\right]} - \lim_{a\uparrow 19} \mathrm{E}\left[D_i \middle| A_i = a\right]$$

In practice, these quantities are estimated via local linear regressions in which the dependent variables are observed insurance status or ED visit rates. The samples for these regressions are limited to be either one year less than age 19 (for $a\uparrow 19$) or one year greater than age 19 (for $a\downarrow 19$). We estimate the sample analogs of the elements of this equation along with the corresponding variance-covariance matrix via Seemingly Unrelated Regression.[21] We then estimate the standard errors via the Delta Method.

In Table 4 we present estimates of the change in insurance coverage at age 19, adjusting for the bias described above. We estimate a 3.3 percent reduction in admissions at age 19 (see Table 5), and this effect shifts the estimated change in the proportion privately insured from –5.0 percentage points to –6.3 percentage points. It also shifts the estimated change in the proportion uninsured from 5.7 percentage points to 8.1 percentage points. The drop in private insurance coverage is complemented by a 1.7 percentage point reduction in the proportion of people covered by Medicaid.[22] The table also presents estimates for men and women separately and reveals that men and women experience similarly sized reductions in insurance coverage.

Figure 6 presents the age profile of the rate of emergency department visits per 10,000 person years. The figure reveals that the rates are increasing throughout this age range for both men and women. The figure also reveals evidence of a discrete reduction in treatment at age 19.[23] In the first column of Table 5 we present the regression estimate of the discrete

[21] The corresponding bias-corrected first stage estimator for the increase in the proportion uninsured at age 19 is $\frac{\lim\limits_{a\downarrow 19} \mathrm{E}\left[U_i \middle| A_i = a\right] \cdot \lim\limits_{a\downarrow 19} \mathrm{E}\left[Y_i \middle| A_i = a\right]}{\lim\limits_{a\uparrow 19} \mathrm{E}\left[Y_i \middle| A_i = a\right]} + \left(1 - \frac{\lim\limits_{a\downarrow 19} \mathrm{E}\left[Y_i \middle| A_i = a\right]}{\lim\limits_{a\uparrow 19} \mathrm{E}\left[Y_i \middle| A_i = a\right]}\right) - \lim\limits_{a\uparrow 19} \mathrm{E}\left[U_i \middle| A_i = a\right]$, where U_i equals one if individual i is uninsured and zero otherwise.

[22] As can be seen in Appendix 13, the estimated magnitudes of the changes in insurance coverage are similar across the five states included in the sample. In addition this table reveals that in three states (Iowa, New Jersey, and Wisconsin) people are aging out of Medicaid at 19.

[23] As a falsification test, we run similar specifications for ED visits at age 20 and find no evidence of either a break in insurance coverage or a change in admissions. These results of this analysis are presented in Appendix

change in the natural log of admissions at age 19 for the entire population and for men and women separately. The regressions reveal that men and women experience a 3.3 percent decrease in visits. [24] Non-pregnant women experience a slightly higher 3.6 percent decrease in visits. In Figure 7 we present the age profile of emergency department visits by hospital type. The figure shows substantial decreases in the number of people treated in emergency departments in non-profit hospitals and for-profit hospitals but no evidence of any decrease in the number of people treated in public hospitals. The corresponding regression estimates are in the second through fourth columns of Table 5. The two classes of privately-controlled hospitals account for almost the entire reduction in the number of people treated.[25]

The reduced-form estimates in Table 5 measure the average change in the probability of visiting the ED at age 19 (see Appendix A). If we assume that losing insurance weakly affects individuals' propensity to visit the ED in one direction, [26] then the reduced-form coefficients estimate the average causal effect of insurance (D_i) for individuals that visit the ED before age 19 and are "compliers" (i.e., lose insurance when turning 19), multiplied by the first-stage estimand (see Appendix A):

$$(8)\quad \hat{\alpha}_1 \xrightarrow{p} \mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0) \mid Y_i(0)=1,\ D_i(1)-D_i(0)=-1\right]\cdot \mathrm{E}\left[D_i(1)-D_i(0) \mid Y_i(0)=1\right].$$

24. We do not perform similar tests at age 18 because it is the age of majority or at age 21 because it is the age at which people are allowed to start purchasing alcohol.

[24] These estimates are fairly robust to bandwidth choice, as can be seen in Appendix 14. In addition the estimates for each of the five states in the sample are not significantly different than the overall estimate of –3.3, as can be seen in Appendix 15.

[25] This is not necessarily evidence of a violation of the Federal Emergency Medical Treatment and Active Labor Act, a federal law that mandates that EDs treat all individuals needing emergency treatment, regardless of ability to pay. It may be that that people choose not to go to the emergency department, decline treatment when they are informed that they lack insurance, or present with conditions that are not emergencies.

[26] The additional "monotonicity" assumption that losing insurance weakly affects individuals' propensity to visit the ED in one direction is not guaranteed to hold. It is possible that losing insurance induces some people to stop visiting the ED but induces others to start. Our reduced-form estimates indicate that the former group dominates the latter group, but the latter group may nevertheless exist. Relaxing the additional monotonicity assumption (referred to as "Extended Monotonicity" in Appendix A), we show that the reduced form estimates a weighted average causal effect for two groups: compliers that visit the ED before age 19 and compliers that visit the ED after age 19 (see Appendix A). We derive a modified first-stage estimator that converges to the sum of the reduced-form weights. Under reasonable assumptions, we establish a lower bound on the magnitude of the average effect of losing insurance on ED visits for compliers that could potentially visit the ED. This lower bound is 0.364, as compared to the estimate of 0.404 reported in this section. Relaxing the Extended Monotonicity assumption thus does not qualitatively change our conclusions.

We can thus estimate the impact of insurance coverage on the use of emergency department services by dividing the estimates of the percent change in admissions from Table 5 by the estimates of the percentage point change in insurance coverage rates from Table 4. This ratio estimates the expected reduction in ED utilization for individuals that visit the ED before age 19 and are compliers. These elasticities are presented in Table 6. The estimate for the overall population is –0.404, implying that individuals that lose their insurance coverage reduce their emergency department visits by 40 percent.[27] The reductions for men and women are very similar.

6. THE EFFECTS OF HEALTH INSURANCE ON INPATIENT ADMISSIONS

Inpatient visits to the hospital are less common than ED visits. Among young adults, approximately 6 percent have had an inpatient admission in the past year. Nevertheless, such visits are expensive; approximately 34 percent of total health care spending is driven by inpatient admissions.[28] As such, the effect of insurance coverage on inpatient visits is a critical object of interest.

To examine the impact of insurance coverage on hospital admissions, we use a census of hospital discharges from six states: Arizona, California, Iowa, New York, Texas, and Wisconsin.[29] Between the six states we observe a total of 849,610 hospital visits among 18 and 19 year olds. These records contain the same demographic variables available in the ED data along with detailed information on the cause of admission and treatment received in the hospital.

We analyze changes in inpatient visits separately for men, pregnant women, and women who are not pregnant. Among young adults, approximately 9.1 percent of women and 2.4 percent of men have an inpatient hospitalization in any given year. The gender difference is almost

[27] As can be seen in Appendix 16, the estimates of the elasticity across the five states in the sample range from -0.586 to -0.191.
[28] Authors' own calculations from the Medical Expenditure Panel Survey.
[29] The hospital records include discharges occurring in the following time periods and states: 2000–2007 in Arizona, 1990–2006 in California, 1990–2006 in New York, 2004–2007 in Iowa, 1999–2003 in Texas and 2004–2007 in Wisconsin. Discharges from hospitals that are not regulated by the states' departments of health services are not included amongst these records.

entirely due to admissions of pregnant women. Women who are pregnant are generally provided with public insurance through Medicaid and thus have a different insurance-age profile than the other two groups. Since there is no change in the proportion uninsured for pregnant women at age 19 (see Table 7), we eliminate these women from our graphical analysis.

Figure 8 presents the age profile of insurance coverage for males and non-pregnant females admitted to a hospital. The figure reveals that the proportion of individuals with private insurance drops with age, while the proportion uninsured or covered by Medicaid increases with age. Overall, the proportion uninsured is far lower than the levels observed in either the general population (as estimated using the NHIS data) or in the population of visitors to the ED. The figure also reveals a decline in private coverage at exactly age 19. This decline is matched by an increase in the proportion uninsured or covered by Medicaid at the same age.[30] Note, however, that the increase in proportion covered by Medicaid is primarily an artifact of the decrease in the total number of inpatient admissions at age 19.[31]

These estimates of the change in insurance coverage at age 19 are biased by a change in composition similar to the one that affects the ED estimates. The first row of Table 7 presents estimates of the discrete change in insurance coverage that occurs at age 19 for the overall inpatient population (including pregnant women), corrected for bias in the manner described in the prior section. The estimates reveal that among all admissions, approximately 41 percent of the loss in private coverage is offset by increases in Medicaid coverage, so that the proportion uninsured increases by only 2.7 percentage points.[32] Most of the increase in Medicaid coverage, however, is concentrated among pregnant women. The other rows of Table 7 present estimates by gender, separating women into pregnant and non-pregnant. These estimates reveal that, for men, aging out of private insurance results in a 6.3 percentage point increase in the proportion that are uninsured. Women who are not

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[30] As can be inferred from the linear age profiles in Figure 8 and can be seen directly in Appendix 17, the estimates of the change in insurance coverage are robust to the choice of bandwidth.

[31] The conclusion that there is little increase in the proportion covered by Medicaid at age 19 (except among pregnant women) is supported by the NHIS and ED results, both of which reveal small declines in Medicaid coverage at age 19.

[32] As can be seen in Appendix 18, the increase in the proportion uninsured is between 2.5 and 3 percentage points in four of the six states in the sample.

pregnant experience an approximately 5.0 percentage point increase in the proportion uninsured. There is little increase in the proportion covered by Medicaid within these two groups.[33] Pregnant women, however, experience little change in the proportion uninsured.[34] For them, Medicaid absorbs most of the loss in private insurance coverage.

In Figure 9 we present the age profile of hospital admissions for men and non-pregnant women by the route through which they are admitted to the hospital. The figure reveals only a small decline in admissions through the emergency department after people lose their insurance coverage. Many of these admissions are for medical conditions that are emergent and may be less sensitive to price. It is also likely that many of these admissions are subject to the Federal Emergency Medical Treatment and Active Labor Act. We see more substantial drops in admissions directly to the hospital. These admissions are typically planned admissions and may be elective. In Table 8 we present estimates of the change in the natural log of admissions at age 19, estimated from equation (2). The table reveals that inpatient admissions through the emergency department drop by about 2 percent for men and 1 percent for non-pregnant women. Inpatient admissions directly to the hospital drop by 6.7 percent for men and 6.0 percent for women.[35,36] Pregnant women exhibit no statistically significant change in hospital admissions. In the bottom three rows of the table we present the estimates of the change in hospital admissions by ownership type. There is a 1.4 percent decrease in admissions to non-profit hospitals and a 4.0 percent decrease in

[33] One of the primary contributions of this paper is that it isolates the effects of uninsured status, avoiding substantial contamination by transitions from private to public insurance. It is thus instructive to compare these "first-stage" results to the "first-stage" results in Card et al. (2008). Among males, the change in uninsured individuals at age 19 is 8.7 times *larger* than the change in Medicaid-covered individuals. Among non-pregnant females, the change in uninsured individuals at age 19 is 4.1 times *larger* than the change in Medicaid-covered individuals. In Card et al. (2008), the change in uninsured individuals at age 65 is 6.3 times *smaller* than the change in Medicare-covered individuals. Thus the private-to-public "contamination problem" is one to two orders of magnitude smaller in this paper than it is in Card et al. (2008).

[34] Most hospitals try to enroll people that are uninsured when they present at the hospital in Medicaid so that they can recover the cost of treating them. Pregnant women are much more likely to qualify for Medicaid than men or non-pregnant women.

[35] Almost all of the reduction in inpatient admissions comes through scheduled admissions, which suggests that the Extended Monotonicity assumption is unlikely to be violated in the inpatient analysis. The Extended Monotonicity assumption could plausibly be violated in the ED data because a lack of primary care might cause a non-serious condition to develop into an emergent condition, necessitating a visit to the ED. However, most of the reduction in inpatient admissions comes through scheduled admissions, which are unlikely to result from emergent conditions. We thus conclude that there is no substantial violation of the Extended Monotonicity assumption in the inpatient data.

[36] As can be inferred from Figure 9 and seen directly in Appendices 19 and 20, these estimates are robust to bandwidth choice. As can be seen in Appendix 21, the estimates vary somewhat across states. The largest reduction in visits is observed in Wisconsin, which also has the largest first-stage effect.

admissions to for profit-hospitals. There is no evidence, however, of a change in overall admissions to hospitals under public control.

In Table 9 we present the instrumental variables estimates of the impact of insurance coverage on the probability of an inpatient admission. The estimate for men is –0.61 and for non-pregnant women is –0.66, implying that losing insurance coverage reduces the probability of an inpatient admission by 61 percent for men and 66 percent for non-pregnant women.[37] These estimates are even larger than the estimates for emergency department visits and suggest that insurance coverage is an important determinant of whether people will receive inpatient treatment. When we examine the results by route into the hospital, it is clear that the overall drop in admissions is due largely to the large decline in admissions directly to the hospital, which are typically elective admissions.

7. DISCUSSION

Three issues affect the generalizability of our regression discontinuity results. First, the estimates are local average treatment effects based on the response of the "compliers", individuals who become uninsured upon turning 19. Second, the estimates are based only on young adults. Third, the estimates represent the short-run response to uninsured status rather than the long-run response. We examine each of these issues below.

7.1 LOCAL AVERAGE TREATMENT EFFECTS

As with all instrumental variables designs, the estimates reported above represent local average treatment effects; they capture the average effect of uninsured status for individuals who lose coverage at age 19. These individuals differ from the typical 19 year old in numerous ways. For example, they are much less likely to attend college (see Figures 2 and 3). Nevertheless, the estimates recover information that is useful for policy makers because the compliers make up a substantial fraction of total uninsured 19 year olds.

[37] As seen in Appendix 22, the estimates vary somewhat across states, though all the precisely estimated elasticities fall between -0.84 and -0.48.

For policy purposes, the parameter of interest is the average effect of insurance coverage for the currently uninsured. The compliers constitute less than 10 percent of total 19 year olds but a much larger share of uninsured 19 year olds. The discontinuities in the NHIS data suggest that almost 20 percent of uninsured 19-year-olds are compliers, and the fraction compliers is even higher in the ED and inpatient data (roughly 25 to 30 percent of uninsured in either case).[38] Furthermore, the age-out mechanism itself affects an even larger fraction of uninsured 19 year olds. Nearly 30 percent of uninsured 19-year-old NHIS respondents report having lost insurance due to age or leaving school, and the total proportion uninsured roughly triples from age 16 to age 22. This suggests that a large fraction of all uninsured young adults have lost insurance in a similar manner.

Of course, a portion of uninsured 19 year olds did not lose insurance through the age out mechanism, and our estimates do not apply directly to them. These chronically uninsured individuals are, in the language of Angrist, Imbens, and Rubin (1996), "never-takers." In most health insurance contexts, a central concern is that insurance coverage choice is intimately related to underlying health; the chronically uninsured (never-takers) may therefore be significantly healthier than the recently uninsured (compliers). Such a relationship would diminish the response of never-takers to insurance coverage relative to compliers. In this case, however, it is unlikely that adverse selection causes a significant divergence in the mean health of never-takers and compliers. This is because the compliers' pre-19 insurance coverage is an artifact of their parents' insurance plans rather than a reflection of their own poor health (if it were not, they would not drop coverage immediately after turning 19). The typical adverse selection mechanism thus does not apply in this context.

Moreover, we find no evidence that never-takers are significantly less healthy or consume less health care than uninsured compliers. To test for any differences, we first use the Medical Expenditure Panel Survey (MEPS), a two-year panel survey of health care

[38] In the NHIS data, we observe a 4.1 percentage point increase in the share uninsured at age 19. Roughly 20 percent of 18-year-olds in the NHIS are uninsured. In the ED and inpatient data, we observe increases in the share uninsured at age 19 of 8.1 percentage points and 2.7 percentage points respectively. Roughly 21.5 percent of 18-year-olds in the ED data are uninsured, and roughly 7.6 percent of 18-year-olds in the inpatient data are uninsured.

consumption. We isolate respondents who enter the survey at age 18 with insurance and then lose insurance during the second year of the survey. Such respondents are likely to be "compliers." We compare these respondents to respondents likely to be never-takers.[39] Though there are few such respondents in the survey, we find no significant differences in either self-reported health or total expenditures in the second year of the survey (when both compliers and never-takers are uninsured).[40]

We confirm the null result in the MEPS with a similar exercise using NHIS data. We isolate all NHIS respondents who are between 18 and 20 years of age and report being uninsured. Using that selected sample, we test for a discontinuity at age 19 in the share of uninsured respondents who report to be in bad health or report a functional limitation that prevents them from certain activities. Such a regression discontinuity would suggest a sudden change in the composition of the uninsured at age 19.[41] We find no such discontinuity, confirming our results from the MEPS. Overall, we find no evidence of significant compositional differences between the compliers and the never-takers.

7.2 Age-Specific Treatment Effects

All regression discontinuity designs estimate treatment effects at a particular threshold. In this case, our estimates apply specifically to individuals close to their 19th birthday, though they are likely to generalize to young adults in their late teens or early twenties.[42] Older individuals may react differently to a loss of health insurance. On the one hand, the overall

[39] Such respondents are 18 years old at the end of the first survey year, and uninsured during both the first and second years of the survey.

[40] Specifically, we find 318 respondents who are "likely compliers" and compare them to 1,070 respondents who are consistently uninsured (never-takers). In a comparison of means, likely compliers are 5.1 percentage points less likely to report being in good health. This difference is statistically insignificant (*t*-statistic of 1.06) and small relative to the proportion of consistently uninsured 18–20 year olds that report being in good health (48.0 percent). Likely compliers also consume 43.61 dollars per year more in health care once uninsured. This difference is again statistically insignificant (*t*-statistic of 0.24) and small relative to the mean health care consumption of consistently uninsured 18–20 year olds (681.46 dollars per year).

[41] For physical limitations, we estimate a statistically insignificant discontinuity of 0.000 (*t*-statistic of 0.00). The mean of the physical limitations variable for 18–20 year olds is 0.036. For bad health, we estimate a statistically insignificant discontinuity of 0.010 (*t*-statistic of 1.00). The mean of the bad health variable for 18–20 year olds is 0.042.

[42] In Appendix 23 we present the estimates of the discrete change in insurance and ED treatment rates that occurs at age 23 when individuals that are still in school age out of their parents' insurance. The change in insurance coverage at age 23 is smaller than the one at age 19, but the difference between the elasticity estimated at age 19 and the one estimated at age 23 is not statistically significant.

utilization of EDs and hospitals is relatively stable until at least age 50 (Figure 1). On the other hand, older adults are susceptible to different medical conditions and may have greater financial resources than uninsured young adults. These factors could affect their response to the provision of health insurance.

We can only speculate as to how the estimates for 19-year-olds translate to the general population. Nevertheless, simple “back-of-the-envelope” calculations suggest that even if the behavioral response estimated above is twice as large as the average response, our results still imply that universal coverage would lead to substantial increases in utilization. In 2005, uninsured individuals constituted 16.7 percent of ED visits and 7.2 percent of inpatient stays (Nawar, Niska, and Xu 2007; DeFrances, Cullen, and Kozak 2007). Suppose therefore that universal coverage generates a 17 percentage point reduction in the share uninsured in EDs and a 7 percentage point reduction in the share uninsured in hospitals. If the elasticities that we estimate for 19-year-olds apply directly to the general population, then universal coverage would generate an 11.4 percent increase in ED visits and an 11 percent increase in inpatient visits. Such an increase, at present levels, amounts to an additional 13.1 million ED visits and 3.8 million inpatient hospital stays each year. Even if our estimates are twice as large as the average response to uninsured status, universal coverage would generate an additional 6.6 million ED visits and 1.9 million inpatient hospital stays each year. Supply constraints might attenuate an overall increase of this magnitude; however, in that case prices would likely rise as well.

7.3 Short Run And Long Run Effects

Our results represent the short-run response to a change in health insurance coverage. The short-run response, however, may differ from the long-run response for three reasons. First, individuals may shift the timing of health care visits across the age 19 threshold. Second, individuals may be able to postpone consumption in the short run but not in the long run. Third, a reduction in preventative care visits may have no impact in the short run but could increase demand for health care in the long run.

The short time horizon in our study may allow individuals to shift the timing of health care visits from the uninsured period to the insured period. When losing insurance, individuals may "stockpile" health care shortly before coverage expires. When gaining insurance, individuals may postpone health care until shortly after coverage begins. In either case, the regression discontinuity we document would be confounded by such behavior. The estimates would reflect the inter-temporal substitution response to a sharp, anticipated change in health care prices and would overstate the net change in health care consumption.

However, there exists little evidence that individuals shift the timing of health care visits in anticipation of gaining or losing insurance coverage. In an analysis of private insurance claims records, Gross (2010) finds no evidence that teenagers who lose coverage at age 19 consume more hospital visits or prescription medication in the weeks before they lose coverage. Card et al. (2008) find no evidence that individuals nearing age 65 postpone inpatient care in significant numbers until they qualify for Medicare, and Long et al. (1998) find little evidence of health care stockpiling for the general population. Additionally, the figures of ED and inpatient visits above do not exhibit an increase in consumption in the months immediately before people turn 19.

A similar estimation problem may arise if individuals postpone care in the hopes of regaining coverage. If newly uninsured 19-year-olds expect to regain insurance coverage within the next six months, for example, they may postpone care until that point. The empirical evidence suggests that this dynamic is not present, however. The age profiles in ED and inpatient care utilization (Figures 6, 7, and 9) show no evidence of postponement. If individuals were postponing care immediately after losing coverage, then we would expect the slope of the age profile to become steeper after age 19. Instead, in every case the slope of the age profile becomes less steep after age 19.

Finally, the RD approach isolates individuals who are insured one day and uninsured the next. As a result, it provides estimates of the effect of health insurance independent from the effect of insurance on health itself. In the long run, though, insults to health accumulate, care may become more critical, and individuals may become less price sensitive. In that case, our estimates could overstate the long-run increase in care that would ensue from an expansion of health insurance coverage. While the long run effect of health insurance on health is an important research question, it is beyond the scope of this paper. To our knowledge, little convincing evidence exists that can quantify the extent to which coverage affects health in the long run.

Nevertheless, a substantial share of the uninsured are without coverage for a short period of time. Among the currently uninsured, 25 percent have been uninsured for less than one year, and 45 percent have been uninsured for less than three years.[43] Our estimates apply directly to this large group of the "recently uninsured."

8. CONCLUSION

We leverage a sharp discontinuity in health insurance coverage that occurs when dependents age out of their parents' insurance plans at age 19. By exploiting that discontinuity, we estimate the effects of health insurance coverage on utilization of care. We find that losing health insurance coverage reduces utilization of both emergency department care and inpatient care. The estimated responses are large – a 10 percentage point decrease in the insurance coverage rate among ED patients reduces ED visits by 4.0 percent, and a 10 percentage point decrease in the insurance coverage rate among hospital patients reduces hospital visits by 6.1 percent. The reduction in hospital visits is stronger for non-urgent admissions, and the reductions in ED and hospital visits are concentrated among for-profit and non-profit hospitals, as opposed to public hospitals.

The net effect of losing health insurance on utilization of care is unambiguously negative for our study population. The results clarify several uncertainties about the impacts of insurance coverage on utilization of care. First, losing insurance coverage results in a net decrease in emergency department care. This suggests that newly uninsured patients do not substitute emergency department care for primary care (or, if they do substitute care towards the emergency department, the substituted care is swamped by a reduction in their normal

[43] These calculations are based on the NHIS. Note that the proportion of uninsured spells that are short-term is even larger than the proportion of currently uninsured individuals who will be short-term uninsured. Cutler and Gelber (2009) find, for example, that from 2001 to 2004, 76 percent of uninsured spells last less than two years among 18 to 61 year olds.

emergency department visits). Second, any increase in uncompensated charity care is insufficient to offset the decrease in paid care, as total ED and inpatient care both fall. Finally, losing insurance does increase the proportion of care that individuals receive at public hospitals. However, this increase is solely due to a decrease in care received at for-profit and non-profit hospitals. The total amount of care at public hospitals does not increase.

Our results apply specifically to young adults that lose insurance coverage by aging out of their parents' insurance plans. Nevertheless, evidence suggests that the coefficients may generalize to the greater population of uninsured young adults, and 19 to 35 year olds comprise over half of uninsured non-elderly adults. Applying our estimated elasticities to all non-elderly adults, we project that near-universal coverage could raise total hospital stays by 3.8 million per year and ED visits by 13.1 million per year, subject to supply constraints. Near-universal coverage would thus increase the amount of care received by currently uninsured individuals and require a substantial increase in net expenditures.

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9. APPENDIX A: ECONOMETRIC THEORY

In this appendix, we present the derivation of the empirical methods that we rely on above. First, recall that our reduced-form regressions involve the logarithm of counts of hospital visits on the left-hand side, and a first-order polynomial of age on the right-hand side (with the sample restricted to individuals within one year of their 19th birthdays). This specification recovers the population-level change in the probability of visiting the hospital at age 19. In particular, note that the structural relationship of interest is:

(A1) $$\log\left(\frac{\sum_i y_{ia}}{N_a}\right) = \alpha_0 + \alpha_1 1\{a > 19\} + f(a) + \varepsilon_a .$$

The left-hand side of equation (A1) represents the probability of having a hospital visit for age group *a* (that is, the total number of visits divided by the total number of individuals in the population of age *a*). Since we rely on administrative records, we do not observe the size of each age group in the underlying population. Instead, we assume that the underlying population at risk for a hospital visit evolves smoothly with age. Under this assumption, we can subtract $\log(N_a)$ from each side of the equation and allow the polynomial $f(a)$ to "absorb" changes in the size of the underlying population. In this way, our primary reduced-form estimating equation involves only simple counts of hospital visits but still captures the change in the *unconditional* probability of a hospital visit at age 19.

The description above justifies our reduced-form approach. But, as described in the main text, a remaining challenge is to consistently estimate both the first stage and the instrumental variables relationships using hospital administrative data. To do so, we rely on a bias correction in the first stage and an additional monotonicity assumption when interpreting the instrumental variables relationship. We demonstrate that, when applied to the ED data, the bias-corrected instrumental variables estimator converges to the average effect of insurance for individuals that lose their insurance coverage at age 19 and visit the ED shortly before age 19.

9.1 NOTATION AND ASSUMPTIONS

Define the instrument Z_i such that $Z_i = 1$ if individual i is encouraged to be uninsured (i.e., is older than the age cutoff threshold) and $Z_i = 0$ if individual i is encouraged to be insured (i.e., is younger than the age cutoff threshold). Define the insurance indicator D_i such that $D_i = 1$ if individual i is insured and $D_i = 0$ if individual i is uninsured. Define the outcome Y_i such that $Y_i = 1$ if individual i visits the ED and $Y_i = 0$ if individual i does not visit the ED.[44] Using the potential outcomes notation from Angrist, Imbens, and Rubin (1996), define $D_i(Z_i)$ such that $D_i(1)$ represents the insurance status of individual i when encouraged to be uninsured and $D_i(0)$ represents the insurance status of individual i when encouraged to be insured. Note that the relationship between D_i and Z_i is *negative*. Define potential outcomes $Y_i(Z_i)$ such that $Y_i(1)$ represents the ED visit indicator for individual i when encouraged to be uninsured and $Y_i(0)$ represents the ED visit indicator for individual i when encouraged to be insured. To represent potential outcomes under different insurance regimes, $Y_i(D_i)$, let $Y_i(D_i = 1)$ represent the ED visit indicator for individual i when insured and $Y_i(D_i = 0)$ represent the ED visit indicator for individual i when uninsured. Finally, define y_0 to be the total number of ED visits pre-19 (i.e., for individuals with $Z_i = 0$), y_1 to be the total number of ED visits post-19 (i.e., for individuals with $Z_i = 1$), d_0 to be the total number of insured ED visits pre-19 (i.e., for individuals with $Z_i = 0$), and d_1 to be the total number of insured ED visits post-19 (i.e., for individuals with $Z_i = 1$). Let N be the total population of individuals (both those that visit the ED and those that do not visit the ED).

We impose the standard LATE monotonicity assumption:

LATE Monotonicity: If $D_i(1) = 1$, then $D_i(0) = 1$.

In other words, if individual i is insured when encouraged to be uninsured, then individual i would also be insured when encouraged to be insured. We define the four potential types of individuals under the LATE Monotonicity assumption as:

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[44] For the following derivations, we assume that the RD bandwidth is small enough that the probability of any individual visiting the ED twice is effectively zero.

LATE Always-takers (LAT): $D_i(0)=1$ and $D_i(1)=1$
LATE Never-takers (LNT): $D_i(0)=0$ and $D_i(1)=0$
LATE Compliers (LC): $D_i(0)=1$ and $D_i(1)=0$
LATE Defiers: $D_i(0)=0$ and $D_i(1)=1$ (ruled out by LATE Monotonicity)

We also impose an Extended Monotonicity assumption that we later relax:

Extended Monotonicity: If $Y_i(1)=1$, then $Y_i(0)=1$.

In other words, if individual *i* visits the ED when encouraged to be uninsured, then individual *i* would also visit the ED when encouraged to be insured. Given the LATE Monotonicity assumption, this assumption is equivalent to assuming that if individual *i* visits the ED when uninsured, then individual *i* would also visit the ED when insured. We define the four potential types of individuals under the Extended Monotonicity assumption as:

Extended Always-takers (EAT): $Y_i(0)=1$ and $Y_i(1)=1$
Extended Never-takers (ENT): $Y_i(0)=0$ and $Y_i(1)=0$
Extended Compliers (EC): $Y_i(0)=1$ and $Y_i(1)=0$
Extended Defiers (EDF): $Y_i(0)=0$ and $Y_i(1)=1$ (ruled out by Extended Monotonicity)

9.1.1 BIAS-CORRECTED FIRST STAGE

We first derive the bias-corrected first stage. Ideally we would estimate $\mathrm{E}[D_i(1)-D_i(0)]$, or the unconditional change in the probability of insurance coverage. However, it is impossible to estimate this quantity using ED data alone, since individuals only appear in these data if they visit the ED. We instead estimate $\mathrm{E}[D_i(1)-D_i(0)\,|\,Y_i(0)=1]$, or the change in the probability of insurance coverage for individuals that visit the ED when encouraged to be insured (i.e., pre-19). Under the LATE Monotonicity assumption,

$\mathrm{E}[D_i(1) - D_i(0) \mid Y_i(0) = 1] = -\mathrm{P}(D_i(1) = 0 \cap D_i(0) = 1 \mid Y_i(0) = 1)$; the decrease in the probability of insurance coverage is equal to the proportion of LATE compliers. To estimate $\mathrm{E}[D_i(1) - D_i(0) \mid Y_i(0) = 1]$, we implement the bias-corrected first stage:

(A2)
$$\frac{d_1}{y_1 + (y_0 - y_1)} - \frac{d_0}{y_0} = \frac{d_1 - d_0}{y_0}$$

We show that this estimator converges to $\mathrm{E}[D_i(1) - D_i(0) \mid Y_i(0) = 1]$.

$$\operatorname{plim}\left(\frac{d_1 - d_0}{y_0}\right) = \operatorname{plim}\left(\frac{d_1/N - d_0/N}{y_0/N}\right)$$
$$= \frac{\mathrm{P}(D_i(1) = 1 \cap Y_i(1) = 1) - \mathrm{P}(D_i(0) = 1 \cap Y_i(0) = 1)}{\mathrm{P}(Y_i(0) = 1)})$$

By Law of Total Probability and LATE Monotonicity:

(A3)
$$= \frac{\mathrm{P}(D_i(1) = 1 \cap Y_i(1) = 1 \cap i \text{ is LAT}) + \mathrm{P}(D_i(1) = 1 \cap Y_i(1) = 1 \cap i \text{ is LNT}) + \mathrm{P}(D_i(1) = 1 \cap Y_i(1) = 1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0) = 1)}$$
$$- \frac{\mathrm{P}(D_i(0) = 1 \cap Y_i(0) = 1 \cap i \text{ is LAT}) + \mathrm{P}(D_i(0) = 1 \cap Y_i(0) = 1 \cap i \text{ is LNT}) + \mathrm{P}(D_i(0) = 1 \cap Y_i(0) = 1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0) = 1)}$$

By the IV exclusion restriction and the definitions of LATE always-takers, LATE never-takers, and LATE compliers:

i is LAT implies: $D_i(1) = D_i(0) = 1$ and $Y_i(1) = Y_i(0)$
i is LNT implies: $D_i(1) = D_i(0) = 0$ and $Y_i(1) = Y_i(0)$
i is LC implies: $D_i(1) = 0$ and $D_i(0) = 1$

Thus equation (A3) equals:

$$= \frac{\mathrm{P}(Y_i(1) = 1 \cap i \text{ is LAT})}{\mathrm{P}(Y_i(0) = 1)} - \frac{\mathrm{P}(Y_i(0) = 1 \cap i \text{ is LAT}) + \mathrm{P}(Y_i(0) = 1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0) = 1)}$$

(A4) $$= -\frac{\mathrm{P}(Y_i(0)=1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)}$$

$$= -\mathrm{P}(i \text{ is LC} \mid Y_i(0)=1)$$

$$= \mathrm{E}\left[D_i(1) - D_i(0) \mid Y_i(0)=1\right]$$

The bias-corrected first stage therefore estimates the probability that an individual is a LATE complier conditional on that individual visiting the ED when encouraged to be insured (i.e., pre-19). Equivalently, it represents a weighted average effect of the age 19 threshold on insurance coverage rates, where the weight for individual *i* is proportional to that individual's probability of visiting the ED just before turning 19. Note that the Extended Monotonicity assumption is not necessary to derive the bias-corrected first stage estimand.

9.1.2 REDUCED FORM

We estimate the percentage decline in visits induced by the instrument (i.e., crossing the "age out" threshold). The reduced form is:

(A5) $$\frac{y_1 - y_0}{y_0}$$

We show that this estimator converges to
$\mathrm{E}\left[Y_i(D_i=1) - Y_i(D_i=0) \mid i \text{ is LC}, Y_i(0)=1\right] \cdot -\mathrm{P}(i \text{ is LC} \mid Y_i(0)=1)$.

$$\mathrm{plim}\left(\frac{y_1 - y_0}{y_0}\right) = \mathrm{plim}\left(\frac{y_1/N - y_0/N}{y_0/N}\right)$$
$$= \frac{\mathrm{P}(Y_i(1)=1) - \mathrm{P}(Y_i(0)=1)}{\mathrm{P}(Y_i(0)=1)}$$

By Law of Total Probability:

$$= \frac{\mathrm{P}(Y_i(1)=1 \cap Y_i(0)=0) + \mathrm{P}(Y_i(1)=1 \cap Y_i(0)=1)}{\mathrm{P}(Y_i(0)=1)} - \frac{\mathrm{P}(Y_i(0)=1 \cap Y_i(1)=0) + \mathrm{P}(Y_i(0)=1 \cap Y_i(1)=1)}{\mathrm{P}(Y_i(0)=1)}$$

By LATE Monotonicity (which implies that $Y_i(1) \neq Y_i(0)$ only for LATE compliers):

$$= \frac{\mathrm{P}(Y_i(1)=1 \cap Y_i(0)=0 \cap i \text{ is LC}) - \mathrm{P}(Y_i(0)=1 \cap Y_i(1)=0 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)}$$

By Bayes' Thoerem:

$$= \frac{\mathrm{P}(Y_i(0)=0 \mid i \text{ is LC} \cap Y_i(1)=1)\cdot \mathrm{P}(i \text{ is LC} \cap Y_i(1)=1) - \mathrm{P}(Y_i(1)=0 \mid i \text{ is LC} \cap Y_i(0)=1)\cdot \mathrm{P}(i \text{ is LC} \cap Y_i(0)=1)}{\mathrm{P}(Y_i(0)=1)}$$

$$= \frac{\mathrm{E}[1-Y_i(0) \mid i \text{ is LC},\ Y_i(1)=1]\cdot \mathrm{P}(i \text{ is LC} \cap Y_i(1)=1) - \mathrm{E}[1-Y_i(1) \mid i \text{ is LC},\ Y_i(0)=1]\cdot \mathrm{P}(i \text{ is LC} \cap Y_i(0)=1)}{\mathrm{P}(Y_i(0)=1)}$$

$$= \frac{\mathrm{E}[Y_i(1)-Y_i(0) \mid i \text{ is LC},\ Y_i(1)=1]\cdot \mathrm{P}(i \text{ is LC} \cap Y_i(1)=1) - \mathrm{E}[Y_i(0)-Y_i(1) \mid i \text{ is LC},\ Y_i(0)=1]\cdot \mathrm{P}(i \text{ is LC} \cap Y_i(0)=1)}{\mathrm{P}(Y_i(0)=1)}$$

(A6)

$$= \mathrm{E}[Y_i(1)-Y_i(0) \mid i \text{ is LC},\ Y_i(1)=1]\cdot \frac{\mathrm{P}(i \text{ is LC} \cap Y_i(1)=1)}{\mathrm{P}(Y_i(0)=1)} - \mathrm{E}[Y_i(0)-Y_i(1) \mid i \text{ is LC},\ Y_i(0)=1]\cdot \frac{\mathrm{P}(i \text{ is LC} \cap Y_i(0)=1)}{\mathrm{P}(Y_i(0)=1)}$$

By Extended Monotonicity, $Y_i(1)=1$ implies $Y_i(0)=1$, so $\mathrm{E}[Y_i(1)-Y_i(0) \mid i \text{ is LC},\ Y_i(1)=1]=0$. Thus equation (A6) equals:

$$= -\mathrm{E}[Y_i(0)-Y_i(1) \mid i \text{ is LC},\ Y_i(0)=1]\cdot \frac{\mathrm{P}(i \text{ is LC} \cap Y_i(0)=1)}{\mathrm{P}(Y_i(0)=1)}$$

(A7) $$= -\mathrm{E}[Y_i(0)-Y_i(1) \mid i \text{ is LC},\ Y_i(0)=1]\cdot \mathrm{P}(i \text{ is LC} \mid Y_i(0)=1)$$

By definition of LATE compliers, $Z_i = 0$ implies $D_i = 1$, and $Z_i = 1$ implies $D_i = 0$. Thus equation (A7) equals:

$$= -\mathrm{E}[Y_i(D_i=1)-Y_i(D_i=0) \mid i \text{ is LC},\ Y_i(0)=1]\cdot \mathrm{P}(i \text{ is LC} \mid Y_i(0)=1)$$

Under the Extended Monotonicity assumption, the reduced form thus estimates the average causal effect of losing insurance on ED visits for LATE compliers that visit the ED pre-19 (i.e., with $Y_i(0)=1$) times the probability of being a LATE complier conditional on visiting the ED pre-19. For completeness, note that $-\mathrm{P}(i \text{ is LC} \mid Y_i(0)=1)$ equals $\mathrm{E}\left[D_i(1)-D_i(0) \mid Y_i(0)=1\right]$.

9.1.3 INSTRUMENTAL VARIABLES ESTIMATOR

The instrumental variables estimator (of which the fuzzy RD is a special case) equals the reduced-form estimator shown in equation (A5) divided by the bias-corrected first-stage estimator shown in equation (A2). It thus converges to:

$$\frac{-\mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0) \mid i \text{ is LC}, Y_i(0)=1\right]\cdot \mathrm{P}(i \text{ is LC} \mid Y_i(0)=1)}{-\mathrm{P}(i \text{ is LC} \mid Y_i(0)=1)}$$
$$=\mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0) \mid i \text{ is LC}, Y_i(0)=1\right]$$

Thus, under the Extended Monotonicity assumption, the IV coefficient estimates the average effect of D_i on Y_i for the subset of LATE compliers that visit the ED when $Z_i=0$ (i.e., that visit the ED pre-19). This is equivalent to a weighted average effect for the entire population of compliers, where the weights are proportional to the probability of visiting the ED pre-19.

9.2 RELAXING THE EXTENDED MONOTONICITY ASSUMPTION

The Extended Monotonicity assumption implies that losing insurance weakly affects individuals' propensity to visit the ED in one direction. This assumption is not guaranteed to hold in the ED data; it is possible that losing insurance induces some people to stop visiting the ED but induces others to start. (The Extended Monotonicity assumption more plausibly holds in the inpatient data used in Section 6; see footnote 35.) We now derive the reduced-form estimand while relaxing the Extended Monotonicity assumption. We then derive the modified first stage that is necessary to rescale the reduced-form estimand.

9.2.1 REDUCED FORM

The reduced form is $\frac{y_1 - y_0}{y_0}$, or the percentage decline in visits induced by the instrument. As shown in equation (A6) above, under LATE Monotonocity $\frac{y_1 - y_0}{y_0}$ converges to:

$$\text{(A8)} \quad \mathrm{E}\left[Y_i(1) - Y_i(0) \mid i \text{ is LC, } Y_i(1) = 1\right] \cdot \frac{\mathrm{P}(i \text{ is LC} \cap Y_i(1) = 1)}{\mathrm{P}(Y_i(0) = 1)}$$
$$-\mathrm{E}\left[Y_i(0) - Y_i(1) \mid i \text{ is LC, } Y_i(0) = 1\right] \cdot \frac{\mathrm{P}(i \text{ is LC} \cap Y_i(0) = 1)}{\mathrm{P}(Y_i(0) = 1)}$$

Note the convergence of the reduced form to equation (A8) does not depend on the Extended Monotonicity assumption. By the definition of LATE complier, equation (A8) equals:

$$= \mathrm{E}\left[Y_i(D_i = 0) - Y_i(D_i = 1) \mid i \text{ is LC, } Y_i(1) = 1\right] \cdot \frac{\mathrm{P}(i \text{ is LC} \cap Y_i(1) = 1)}{\mathrm{P}(Y_i(0) = 1)}$$
$$-\mathrm{E}\left[Y_i(D_i = 1) - Y_i(D_i = 0) \mid i \text{ is LC, } Y_i(0) = 1\right] \cdot \frac{\mathrm{P}(i \text{ is LC} \cap Y_i(0) = 1)}{\mathrm{P}(Y_i(0) = 1)}$$

$$\text{(A9)} \quad = \mathrm{E}\left[Y_i(D_i = 1) - Y_i(D_i = 0) \mid i \text{ is LC, } Y_i(0) = 1\right] \cdot \frac{-\mathrm{P}(i \text{ is LC} \cap Y_i(0) = 1)}{\mathrm{P}(Y_i(0) = 1)}$$
$$+\mathrm{E}\left[Y_i(D_i = 1) - Y_i(D_i = 0) \mid i \text{ is LC, } Y_i(1) = 1\right] \cdot \frac{-\mathrm{P}(i \text{ is LC} \cap Y_i(1) = 1)}{\mathrm{P}(Y_i(0) = 1)}$$

Under LATE Monotonicity, the reduced form estimates a weighted sum of two average causal effects of D_i on Y_i. The first is the average causal effect of losing insurance for LATE compliers that visit the ED pre-19 (i.e., that have $Y_i(0) = 1$). The second is the average causal effect of losing insurance for LATE compliers that visit the ED post-19 (i.e., that have $Y_i(1) = 1$). Note that these two groups are not mutually exclusive; individuals that are "extended always-takers" appear in both groups.

9.2.2 MODIFIED FIRST STAGE

The goal of the modified first stage is to recover the weights in the reduced form above. The original bias-adjusted first stage converged to $-\mathrm{P}(i \text{ is LC} \mid Y_i(0) = 1)$ (which is identical to the first of the two weights above). We modify the first stage so that it now estimates the sum of the two weights above. The modified first stage is:

$$\text{(A10)} \qquad \frac{2(d_1 - d_0)}{y_0} + \frac{(y_0 - y_1)}{y_0}$$

From the derivation of the original bias-adjusted first stage, the first term of equation (A10) converges to twice the quantity shown in equation (A4):

$$\operatorname{plim}\left(\frac{2(d_1 - d_0)}{y_0}\right) = -\frac{2\cdot \mathrm{P}(Y_i(0) = 1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0) = 1)}$$

The last term of equation (A10) converges to:

$$\operatorname{plim}\left(\frac{y_0 - y_1}{y_0}\right) = \operatorname{plim}\left(\frac{y_0/N - y_1/N}{y_0/N}\right)$$

$$= \frac{\mathrm{P}(Y_i(0) = 1) - \mathrm{P}(Y_i(1) = 1)}{\mathrm{P}(Y_i(0) = 1)}$$

$$\text{(A11)} \quad = \frac{\mathrm{P}(Y_i(0) = 1 \cap i \text{ is LAT}) + \mathrm{P}(Y_i(0) = 1 \cap i \text{ is LNT}) + \mathrm{P}(Y_i(0) = 1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0) = 1)}$$

$$- \frac{\mathrm{P}(Y_i(1) = 1 \cap i \text{ is LAT}) + \mathrm{P}(Y_i(1) = 1 \cap i \text{ is LNT}) + \mathrm{P}(Y_i(1) = 1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0) = 1)}$$

By the IV exclusion restriction and the definitions of LATE always-takers and LATE never-takers, "*i* is LAT" or "*i* is LNT" imply that $Y_i(0) = Y_i(1)$. Thus equation (A11) equals:

$$= \frac{\mathrm{P}(Y_i(0) = 1 \cap i \text{ is LC}) - \mathrm{P}(Y_i(1) = 1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0) = 1)}$$

The modified first stage shown in equation (A10) thus converges to:

$$\operatorname{plim}\left(\frac{2(d_1 - d_0)}{y_0} + \frac{y_0 - y_1}{y_0}\right) = -\frac{2\cdot \mathrm{P}(Y_i(0) = 1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0) = 1)} + \frac{\mathrm{P}(Y_i(0) = 1 \cap i \text{ is LC}) - \mathrm{P}(Y_i(1) = 1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0) = 1)}$$

$$(\text{A12}) \quad = -\frac{\text{P}(Y_i(0)=1 \cap i \text{ is LC}) + \text{P}(Y_i(1)=1 \cap i \text{ is LC})}{\text{P}(Y_i(0)=1)}$$

The modified first stage, equation (A10), therefore estimates the sum of the weights from the reduced form.

9.2.3 MODIFIED INSTRUMENTAL VARIABLES ESTIMATOR

The modified instrumental variables estimator equals the reduced form estimator shown in equation (A5) divided by the modified first-stage estimator shown in equation (A10). It thus converges to:

$$\text{E}\left[Y_i(D_i=1) - Y_i(D_i=0) \mid i \text{ is LC},\ Y_i(0)=1\right] \cdot \frac{\text{P}(i \text{ is LC} \cap Y_i(0)=1)}{\text{P}(Y_i(0)=1 \cap i \text{ is LC}) + \text{P}(Y_i(1)=1 \cap i \text{ is LC})}$$

$$+\text{E}\left[Y_i(D_i=1) - Y_i(D_i=0) \mid i \text{ is LC},\ Y_i(1)=1\right] \cdot \frac{\text{P}(i \text{ is LC} \cap Y_i(1)=1)}{\text{P}(Y_i(0)=1 \cap i \text{ is LC}) + \text{P}(Y_i(1)=1 \cap i \text{ is LC})}$$

Thus, when relaxing the Extended Monotonicity assumption, the modified instrumental variables estimator converges to a weighted average of two average causal effects of D_i on Y_i. The first is the average causal effect of losing insurance for LATE compliers that visit the ED pre-19 (i.e., that have $Y_i(0)=1$). The second is the average causal effect of losing insurance for LATE compliers that visit the ED post-19 (i.e., that have $Y_i(1)=1$). Note that these two groups are not mutually exclusive. In particular, both groups contain LATE compliers that would visit the ED regardless of insurance status. Thus the average is skewed towards this group, but for this group insurance status has no causal effect on ED visits. The modified instrumental variables estimand is thus attenuated relative to the expected effect of increasing health insurance coverage for all LATE compliers.

9.2.4 ESTIMATES FROM EMERGENCY DEPARTMENT DATA

The modified first-stage, equation (A10), is equal to –0.126 in the ED data.[45] The modified first stage thus generates a modified IV estimate of 0.263, as compared to the original IV

[45] We count privately insured patients, Medicaid patients, and "other insurance" patients as insured. Taking the estimates from Tables 5 and 6, equation (A10) thus equals 2*(–0.628 – 0.0166 –0.0015) + 0.033 = –0.126.

estimate of 0.404. However, as noted in Section 9.2.3, this estimate is attenuated in the sense that it places double weight on individuals that visit the ED regardless of insurance status ("extended always-takers"), because for these individuals $Y_i(0)=1$ and $Y_i(1)=1$. To see that these individuals receive double weight, note that the reduced form estimand, equation (A9), can be rewritten as:

$$\mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC},\ Y_i(0)=1\right]\cdot\frac{-\mathrm{P}(i\text{ is LC}\cap Y_i(0)=1)}{\mathrm{P}(Y_i(0)=1)}$$

$$+\mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC},\ Y_i(1)=1\right]\cdot\frac{-\mathrm{P}(i\text{ is LC}\cap Y_i(1)=1)}{\mathrm{P}(Y_i(0)=1)}$$

$$=\Big\{\mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC},\ i\text{ is EAT}\right]\cdot \mathrm{P}(i\text{ is EAT}\mid i\text{ is LC},\ Y_i(0)=1)$$

$$+\mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC},\ i\text{ is EC}\right]\cdot \mathrm{P}(i\text{ is EC}\mid i\text{ is LC},\ Y_i(0)=1)\Big\}$$

$$\cdot\frac{-\mathrm{P}(i\text{ is LC}\cap Y_i(0)=1)}{\mathrm{P}(Y_i(0)=1)}$$

$$+\Big\{\mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC},\ i\text{ is EAT}\right]\cdot \mathrm{P}(i\text{ is EAT}\mid i\text{ is LC},\ Y_i(1)=1)$$

$$+\mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC},\ i\text{ is EDF}\right]\cdot \mathrm{P}(i\text{ is EDF}\mid i\text{ is LC},\ Y_i(1)=1)\Big\}$$

$$\cdot\frac{-\mathrm{P}(i\text{ is LC}\cap Y_i(1)=1)}{\mathrm{P}(Y_i(0)=1)}$$

$$=\mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC},\ i\text{ is EAT}\right]\cdot\frac{-\mathrm{P}(i\text{ is EAT}\cap i\text{ is LC}\cap Y_i(0)=1)}{\mathrm{P}(Y_i(0)=1)}$$

$$+\mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC},\ i\text{ is EC}\right]\cdot\frac{-\mathrm{P}(i\text{ is EC}\cap i\text{ is LC}\cap Y_i(0)=1)}{\mathrm{P}(Y_i(0)=1)}$$

$$+\mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC},\ i\text{ is EAT}\right]\cdot\frac{-\mathrm{P}(i\text{ is EAT}\cap i\text{ is LC}\cap Y_i(1)=1)}{\mathrm{P}(Y_i(0)=1)}$$

$$+\mathrm{E}\left[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC},\ i\text{ is EDF}\right]\cdot\frac{-\mathrm{P}(i\text{ is EDF}\cap i\text{ is LC}\cap Y_i(1)=1)}{\mathrm{P}(Y_i(0)=1)}$$

The extended always-takers (EAT) appear twice because they visit the ED both when insured and uninsured. By definition, however, $Y_i(D_i=1)=Y_i(D_i=0)=1$ for extended always-takers, so either of the conditional expectations involving extended always-takers can be eliminated. Thus the reduced form also converges to:

$$\text{(A13)}\quad \mathrm{E}\big[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC, } i \text{ is EAT}\big]\cdot \frac{-\mathrm{P}(i \text{ is EAT} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)}$$

$$+\mathrm{E}\big[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC, } i \text{ is EC}\big]\cdot \frac{-\mathrm{P}(i \text{ is EC} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)}$$

$$+\mathrm{E}\big[Y_i(D_i=1)-Y_i(D_i=0)\mid i \text{ is LC, } i \text{ is EDF}\big]\cdot \frac{-\mathrm{P}(i \text{ is EDF} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)}$$

The reduced form therefore estimates a weighted average of three average causal effects: the average causal effect for LATE compliers who are extended always-takers, the average causal effect for LATE compliers who are "extended compliers" (individuals that visit the ED only when insured), and the average causal effect for LATE compliers who are "extended defiers" (individuals that visit the ED only when uninsured). These three mutually exclusive groups exhaust the population of LATE compliers that visit the ED. Each group's weight is proportional to its share of LATE compliers that visit the ED either before or after age 19 (i.e., LATE compliers who are not extended never-takers). With estimates of the weights in equation (A13), we can recover the average causal effect of insurance for LATE compliers that visit the ED before or after age 19.

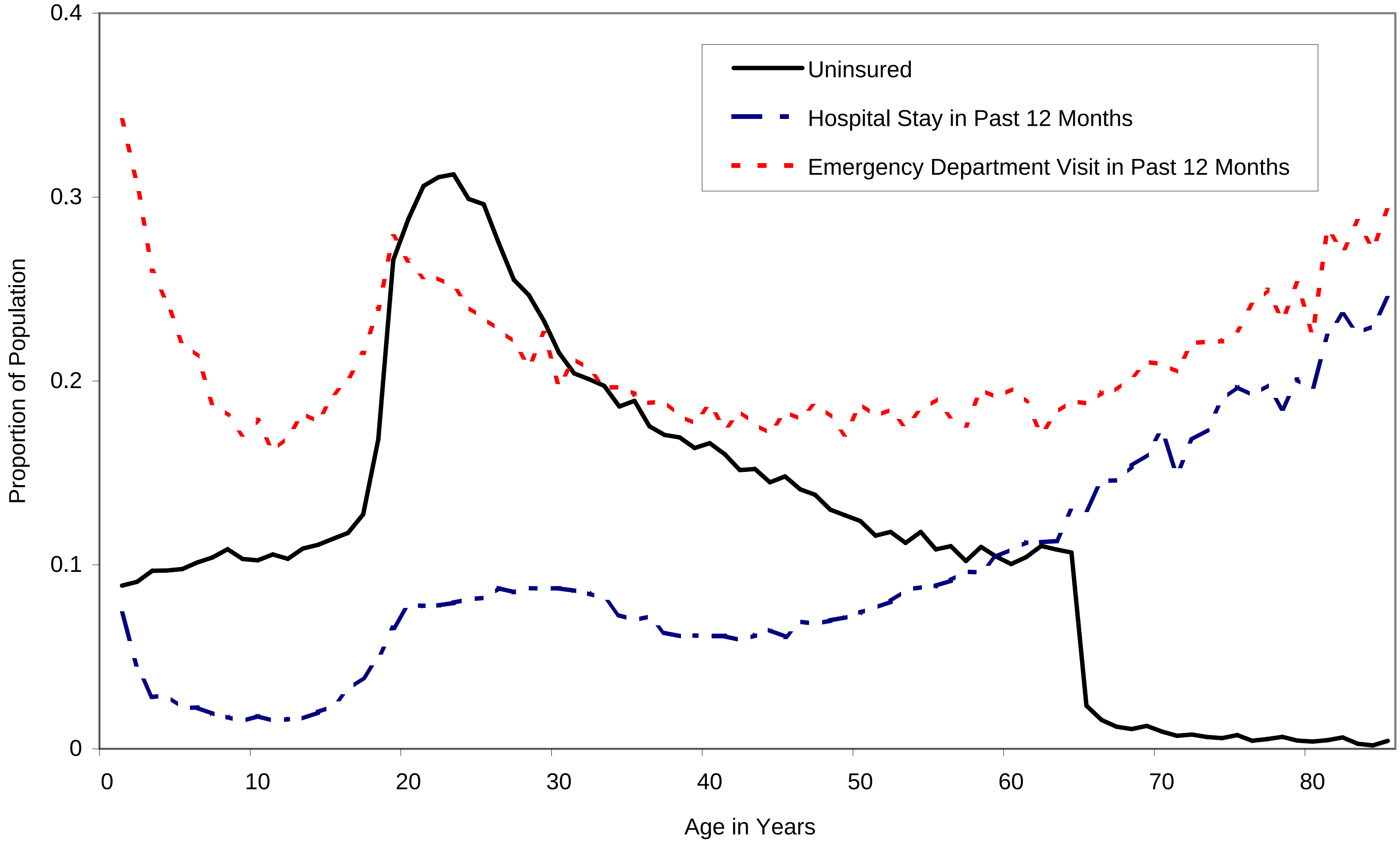
It is impossible, however, to identify exactly what portion of LATE compliers are extended always-takers versus extended compliers or extended defiers. But note that from equation (A4), the original bias-corrected first stage (equation (A2)) estimates

$-\frac{\mathrm{P}(Y_i(0)=1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)} = -\left(\frac{\mathrm{P}(i \text{ is EAT} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)} + \frac{\mathrm{P}(i \text{ is EC} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)}\right)$, or the sum of the first two weights in equation (A13). As reported in Table 4, this quantity equals 0.081. Likewise, equations (A12) and (A4) imply that the difference between the modified bias-corrected first stage (equation (A10)) and the original bias-corrected first stage (equation (A2)) estimates

$-\frac{\mathrm{P}(Y_i(1)=1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)} = -\left(\frac{\mathrm{P}(i \text{ is EAT} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)} + \frac{\mathrm{P}(i \text{ is EDF} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)}\right)$, or the sum of the first and third weights in equation (A13). This quantity is 0.045 (given by 0.126 – 0.081 = 0.045). However, equation (A13) has three unknown quantities, and we have only two linearly independent estimates, equations (A2) and (A10). We must therefore make an additional assumption to derive a bound on the sum of the weights in equation (A13).

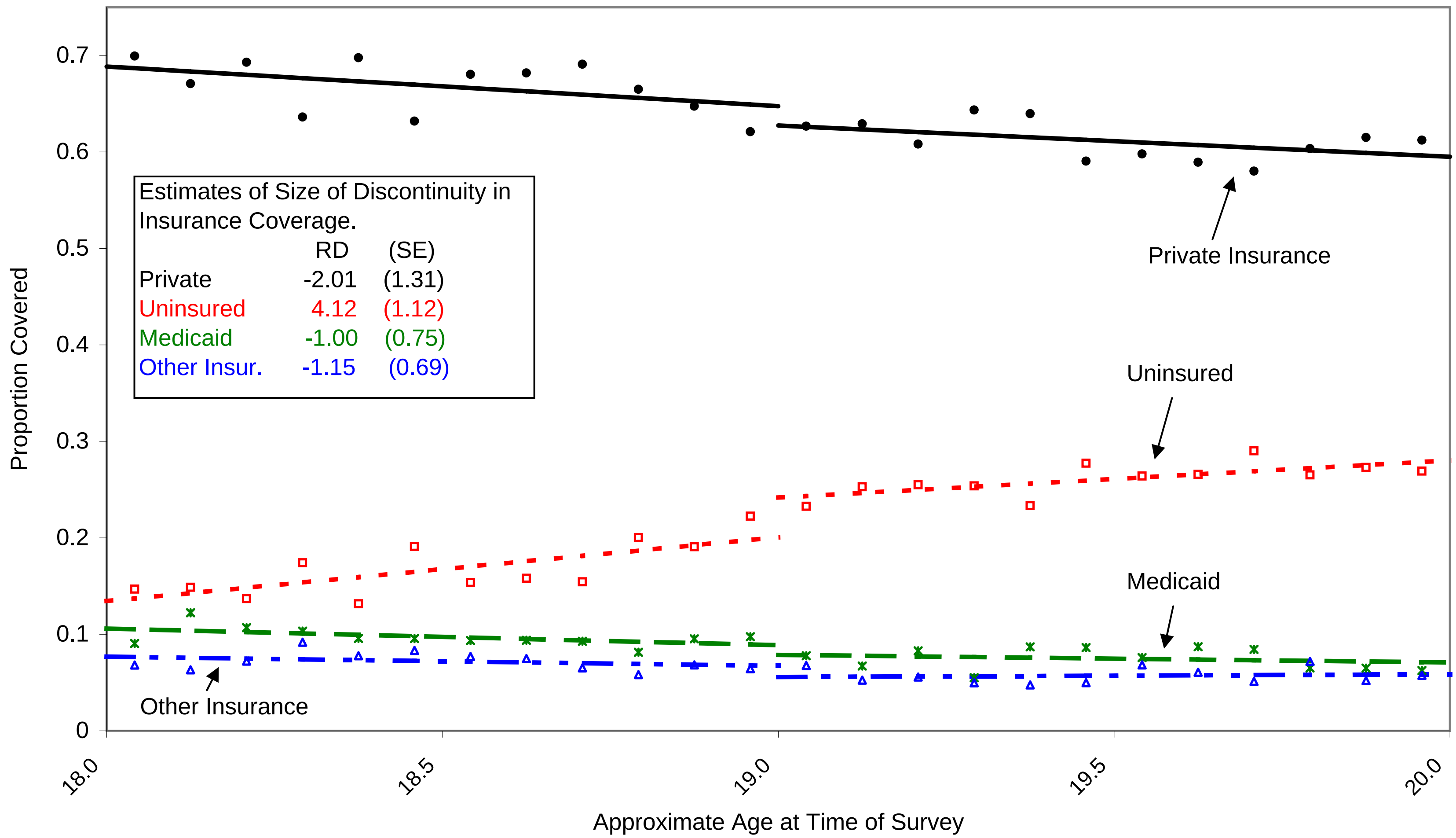
To establish an upper bound (in magnitude) on the sum of the three weights in equation (A13), we make the reasonable assumption that the number of LATE compliers that stop visiting the ED when becoming uninsured (extended compliers) is no greater than the number of LATE compliers that either continue to visit the ED when becoming uninsured or begin visiting the ED when becoming uninsured (extended always-takers plus extended defiers). In other words, we assume that the number of newly uninsured that stop visiting the ED is no greater than the number of newly uninsured that continue visiting the ED plus the number of newly uninsured that begin visiting the ED. Under this assumption, $\frac{\mathrm{P}(i \text{ is EC} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)}$ is at most 0.045, and thus $\frac{\mathrm{P}(i \text{ is EAT} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)}$ is at least 0.036 (given by 0.081 – 0.045 = 0.036). We therefore adjust the modified first-stage estimator for double counting of extended always-takers by subtracting at least 0.036, and find that the modified first-stage estimator has an upper bound (in magnitude) of 0.090 (given by 0.126 – 0.036 = 0.090). A modified first-stage of –0.090 generates a modified IV estimate of 0.364. We thus conclude that losing insurance coverage reduces the probability of an ED visit for LATE compliers that could potentially visit the ED by at least 36 percent.

Figure 1: Age Profile of Proportion Uninsured, ED visits and Hospital Stays



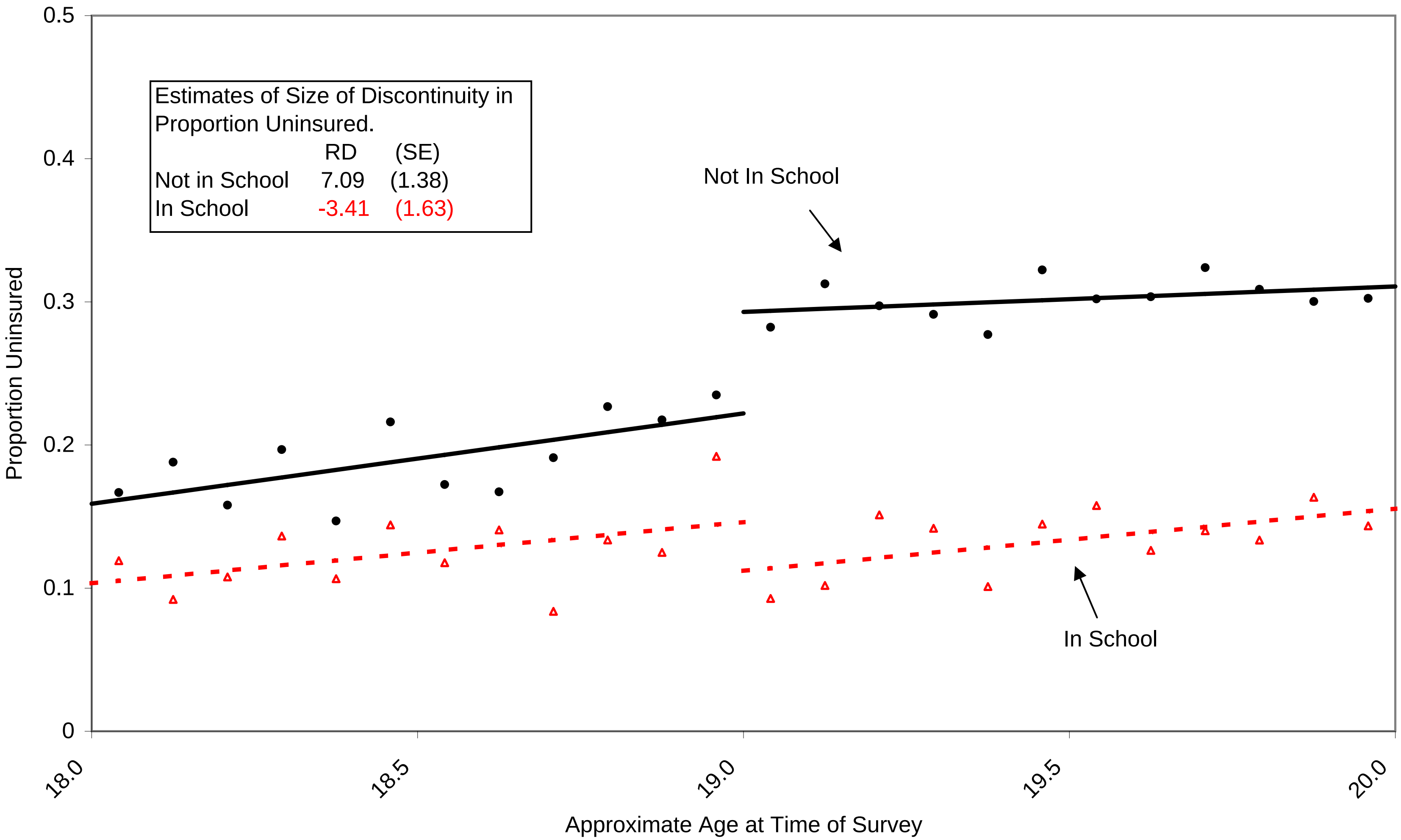
Notes: These estimates are derived from the NHIS 1997-2007.

Figure 2: Age Profile of Health Insurance Coverage in the United States
National Health Interview Survey (1997-2007)



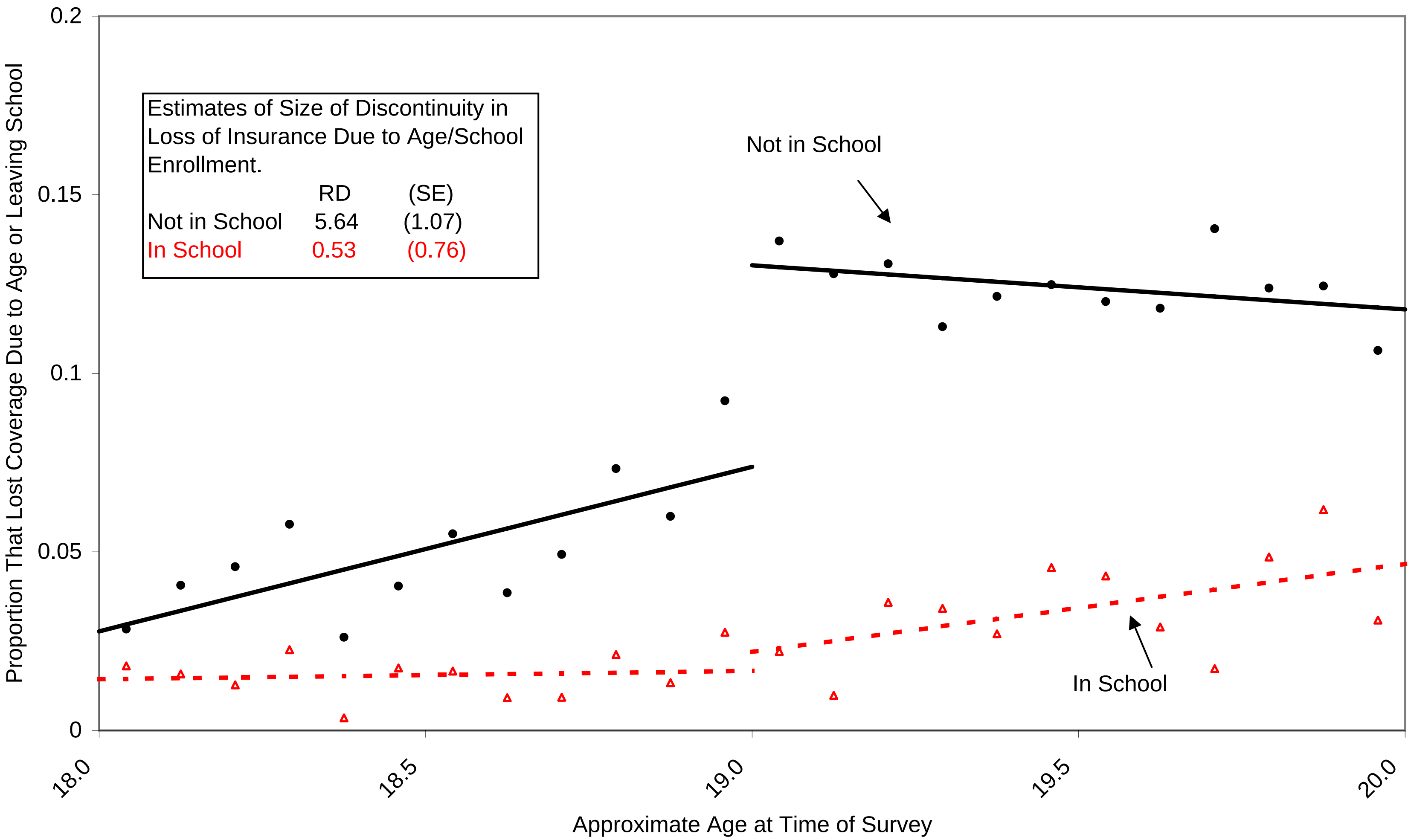
Notes: Regressions and proportions are weighted to take into account the stratified structure of the NHIS. The regression lines superimposed on the proportions are from a linear polynomial in age interacted with a dummy that takes on a value of one for people over 19 and 0 otherwise. This regression is fit on the micro data rather than the means of the bins. The age variable is centered on the last day of the month on which the individual's 19th birthday falls. Individuals with unknown month of birth comprise 11.1 percent of the surveyed population that are 18 or 19 at the time of the survey and they have been dropped from the analysis. The age profiles above include 24,260 individuals from the NHIS person files.

Figure 3: Age Profile of Proportion Uninsured by School Attendance
National Health Interview Survey (1997-2007)



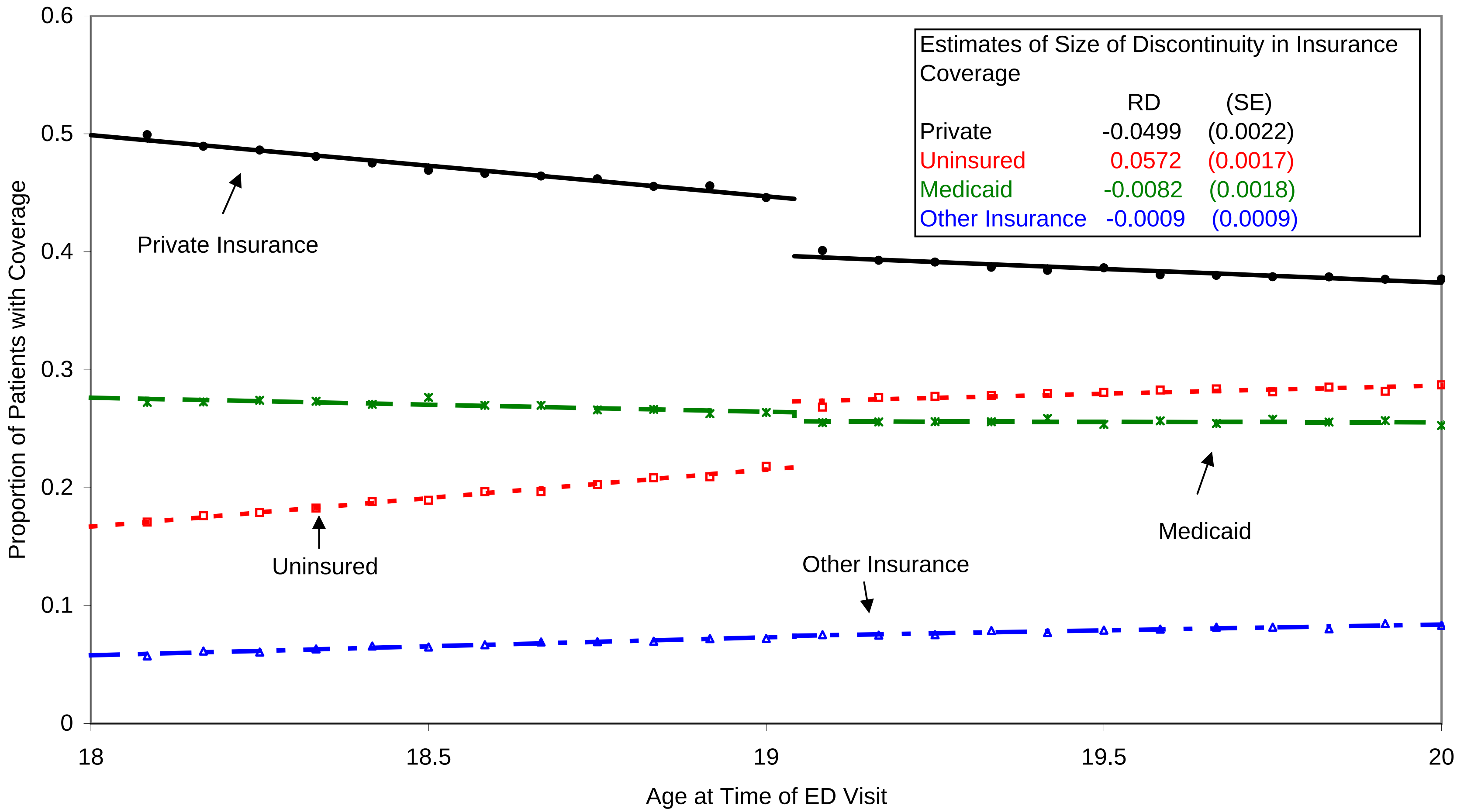
Notes: See notes from Figure 2. As can be inferred from how the proportions vary around the fitted lines the "In School" group is shrinking with age and the "Not in School" group is growing, however there is no discrete change at age 19 in the mix of these groups. There are 17,058 individuals coded as not in school and 7,202 coded as in school.

Figure 4: Age Profile of Loss of Insurance Due to Age or Leaving School by School Attendance
National Health Interview Survey (1997-2007)



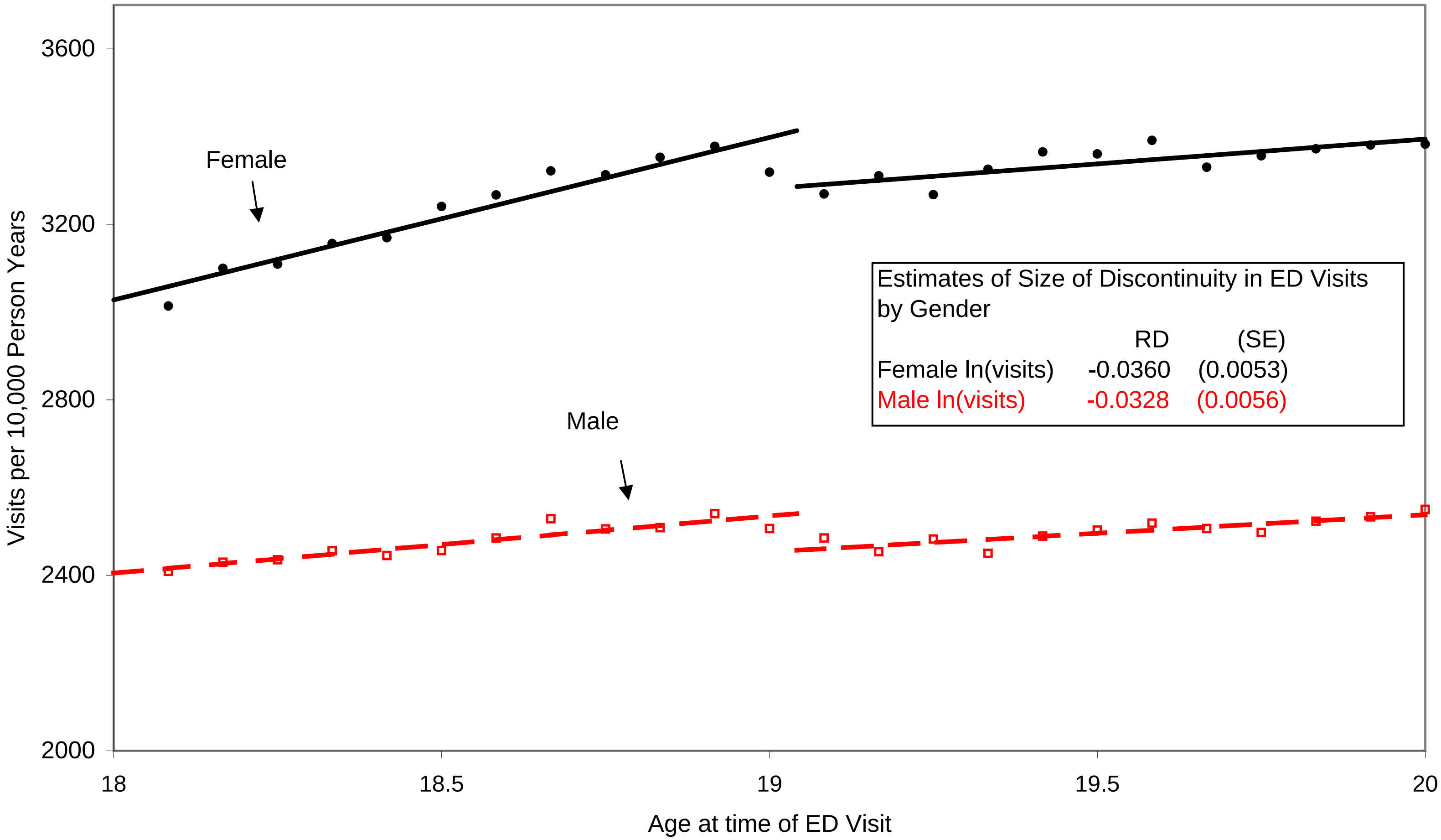
Notes: See notes from Figure 2. In the National Health Interview Survey the respondent is asked the following question regarding all household members that are currently without health insurance. "Which of these are reasons (you/subject name) stopped being covered or do not have health insurance?" One possible answer they can choose from is "Ineligible because of age/left school".

Figure 5: Age Profile of Insurance Coverage for People Entering the Emergency Department



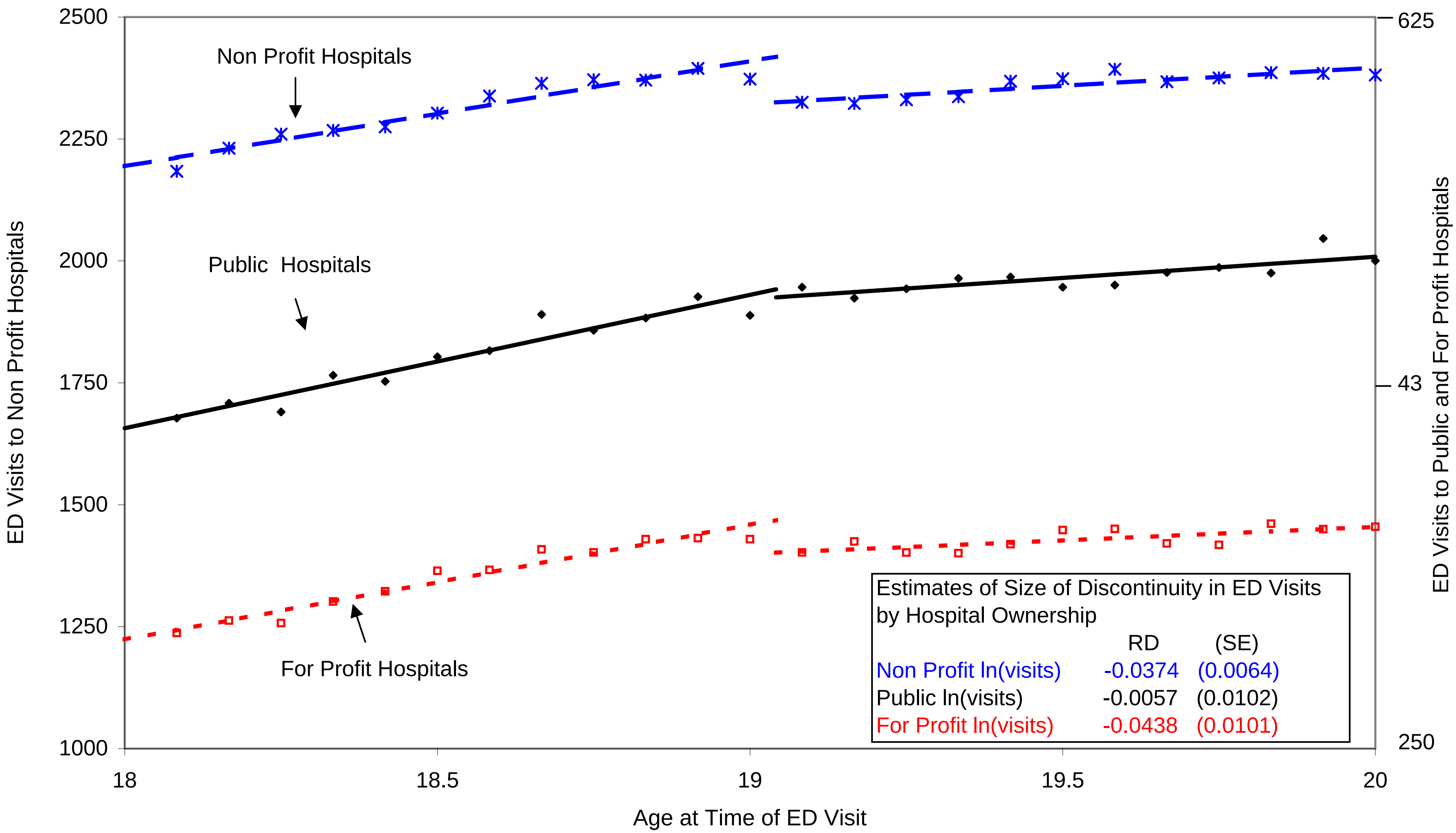
Notes: The Emergency Department datasets used to make the age profiles above are a near census of ED visits in Arizona (2005-2007), California (2005-2007), Iowa (2004-2007), New Jersey (2004-2007) and Wisconsin (2004-2007). Only hospitals that are not under state oversight do not contribute data. The sample includes 1,744,394 ED visits by individuals either 18 or 19 years old. The dependant variable in the regressions is the proportion of individuals that lack health insurance.

Figure 6: Age Profile of Emergency Department Visits by Gender



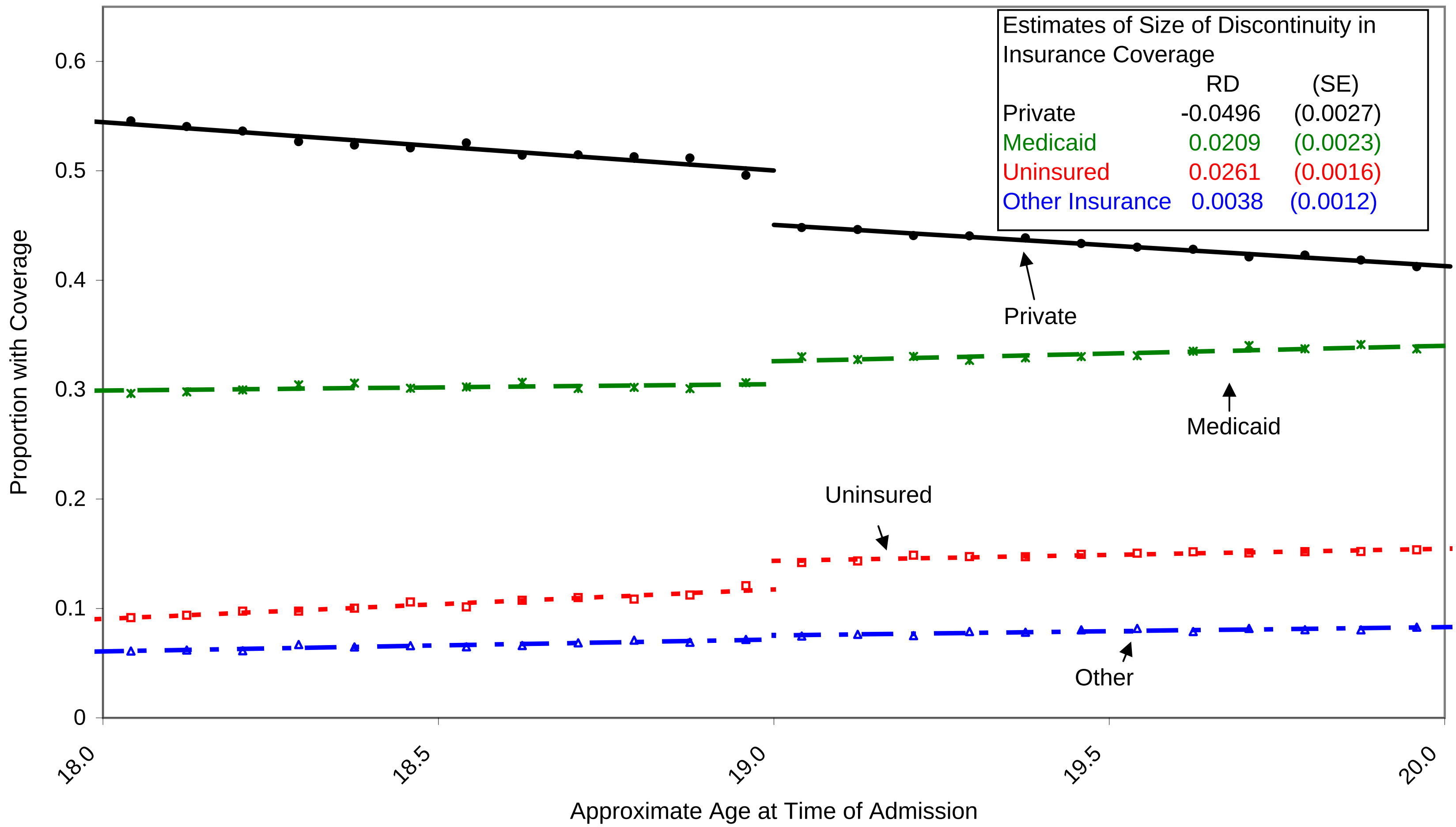
Notes: See notes from Figure 5. The age profiles are in rates per 10,000 person years. The dependant variable for the regression estimates is the natural log of the admission counts. The female category does not include pregnant women (13.5% of ED visits). Patients that present at the ED and are admitted to the hospital are drawn from hospital discharge records and included in the analysis.

Figure 7: Age Profile of Emergency Department Visits By Ownership of Hospital



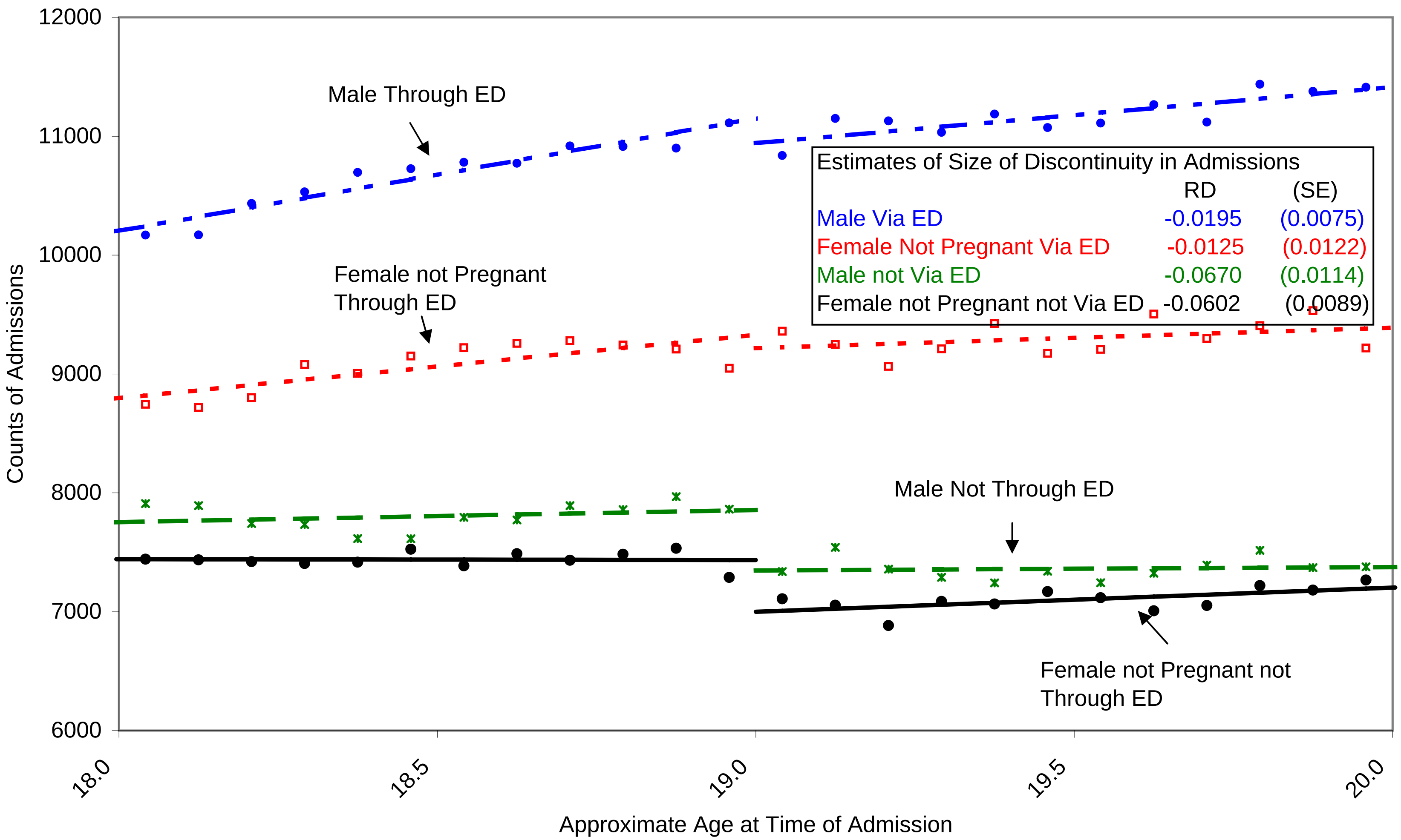
Notes: See notes from Figure 6. Approximately 1.4 percent of people are admitted to hospitals of unknown ownership type.

Figure 8: Age Profile of Insurance Coverage for Hospital Admissions



Notes: The hospital discharge datasets used to make the age profiles include a near census of hospital stays in Arizona (2000-2007), California (1990-2006), Iowa (2004-2007), New York (1990-2006), Texas (1999-2003) and Wisconsin (2004-2007). Women that are pregnant have been dropped from the sample. Combining the data from the six states gives a sample of 849,610 18 and 19 year olds. Each of the points plotted above is the proportion of people with a particular type of coverage. The lines are the fitted values from a linear regression fitted to the points on either side of the age 19 cut off.

Figure 9: Hospital Admissions by Gender and Route into Hospital



Notes: See notes from Figure 8. Each of the points plotted above is the number of people admitted to the hospital at a particular month in age. The line laying over the points is the fitted values from a linear regression estimated from the observations on either side of the age 19 cut off. The point estimate in the box is the estimate from a regression with the same specification but the dependant variable is the natural log of the counts.

Table 1: Differences Between Insured and Uninsured Young Adults
(National Health Interview Survey 1997-2007)

	Insured	Uninsured	Difference Between Insured and Uninsured	T-stat for Difference in Means	Regression Estimates of Discrete Jump at 19 (1 year Bandwidth)	T-statistic for difference in RD
	(1)	(2)	(3)	(4)	(5)	(6)
Employed	52.1	55.0	3.0	3.4	-2.4	-1.7
In School	33.3	17.9	-15.4	-18.6	1.0	0.7
Percent Days Drinking	5.9	5.9	0.0	-0.1	0.2	0.4
Smoker	20.5	33.8	13.3	8.7	-0.3	-0.2
Flu Shot Last 12 Months	15.5	10.2	-5.4	-4.7	-2.2	-1.2
Married	3.5	7.7	4.2	9.1	-0.5	-1.0
White	70.2	50.0	-20.2	-22.0	3.8	2.7
Black	13.5	16.1	2.7	3.9	-1.1	-1.0
Hispanic	10.8	28.7	18.0	25.0	-1.5	-1.7
Male	49.2	53.7	4.6	5.3	-1.1	-0.7

Notes: All the estimates in the table are based on a dataset created by stacking the NHIS Person Files and Sample Adult Files for the 1997-2007 survey years. All the estimates are presented in percents. The estimates are weighted and the standard errors are adjusted to account for the stratified sampling frame. The outcomes Flu Shot, Smoker and Percent Days Drinking are coded from the NHIS Sample Adult files 1997-2007 which include 8,121 respondents surveyed within 12 months of their 19th birthday. The remaining variables are coded from the NHIS Person file 1997-2007 which includes 24,260 respondents surveyed within 12 months of their 19th birthday. The regression discontinuity estimates in the column 5 and its t-statistic in column 6 are from a linear polynomial interacted with an indicator variable for over 19 estimated from all respondents surveyed within 12 months of their 19th birthday.

Table 2: Change in Distribution of Insurance Coverage at Age 19

	Private Insurance		Uninsured		Medicaid		Other Insurance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All	-2.01	-2.49	4.12	4.61	-1.00	-1.03	-1.15	-1.13
	[1.31]	[1.23]	[1.12]	[1.09]	[0.75]	[0.72]	[0.69]	[0.7]
	64.76		20.06		8.87		6.73	
	-5.33	-5.05	7.09	7.11	-0.06	-0.34	-1.86	-1.89
Not in School	[1.6]	[1.52]	[1.38]	[1.37]	[0.91]	[0.88]	[0.89]	[0.89]
	62.31		22.21		8.53		7.44	
	6.21	4.13	-3.41	-2.29	-3.04	-2.33	0.48	0.74
In School	[2.12]	[2.05]	[1.63]	[1.63]	[1.30]	[1.25]	[1.20]	[1.20]
	70.99		14.62		9.54		5.16	
Covariates	No	Yes	No	Yes	No	Yes	No	Yes

Notes: For each population above the table includes an estimate of the discrete change in the variable that occurs at age 19 with its standard error in brackets below. The regressions are estimates via a linear probability model and the point estimates have been multiplied by 100 to put them in percentage points. Underneath the standard error we include an estimate of the average level of the variable just before people turn 19. The regressions all include a dummy for over age 19 and a linear term in age interacted with the dummy. The regressions are weighted to take into account the stratified sampling frame in the NHIS. The second regression of each pair includes the following covariates Hispanic, black, male, employed, attending school and married. The regressions estimated using the subpopulation of respondents that are not in school do not include the indicator variable for attending school. The regression estimated using respondents that are in school do not include the indicator variable for attending school or the indicator variable for employed. The regressions include all young adults surveyed within 12 months of their 19th birthday of which there are 24,260 in the NHIS person files between 1997 and 2007 for whom month of birth is available (11.1% of people in this approximate age range do not have a recorded month of birth). Respondents were asked if they had a job or were looking for work. Those that responded they weren't could choose among several explanations one of which was "going to school". We coded people who responded "Going to School" as in school though it is clear the pattern of questions makes it likely that some individuals that are in school will be coded as not in school. Of the individuals with birth months available 17,058 are coded as not in school and 7,202 are coded as in school.

Table 3: Cause of Insurance Loss and Source of Coverage

	Lost Insurance Due to Age		Insurance in Own Name	
	(1)	(2)	(3)	(4)
All	4.30	4.32	-0.67	-0.52
	[0.8]	[0.79]	[0.67]	[0.68]
	5.69		5.10	
	5.64	5.51	-1.01	-0.85
Not in School	[1.07]	[1.06]	[0.86]	[0.87]
	7.38		6.35	
	0.53	0.73	0.27	0.18
In School	[0.76]	[0.75]	[0.88]	[0.89]
	1.67		2.23	
Covariates	No	Yes	No	Yes

Notes: See notes from Table 2. In the National Health Interview Survey the respondent is asked the following question regarding all household members that are currently without health insurance. "Which of these are reasons (you/subject name) stopped being covered or do not have health insurance?" One possible answer they can choose from is "Ineligible because of age/left school". Respondents that report having health insurance are asked if the insurance is in their own name or someone else's name.

Table 4: Change at Age 19 in Insurance Coverage of Emergency Department Visits

	Private	Uninsured	Medicaid	Other Insurance
	(1)	(2)	(3)	(4)
All	-0.0628	0.0810	-0.0166	-0.0015
	[0.0026]	[0.0046]	[0.0024]	[0.0010]
	0.4471	0.2154	0.2644	0.0731
All (Except Pregnant)	-0.0628	0.0842	-0.0200	-0.0014
	[0.0027]	[0.0048]	[0.0024]	[0.0011]
	0.4647	0.2178	0.2417	0.0759
Male	-0.0657	0.0831	-0.0191	0.0017
	[0.0035]	[0.0050]	[0.0026]	[0.0015]
	0.4632	0.2479	0.1949	0.0941
Female	-0.0605	0.0791	-0.0156	-0.0030
	[0.0030]	[0.0056]	[0.0032]	[0.0012]
	0.4336	0.1942	0.3159	0.0563
Female Not Pregnant	-0.0597	0.0844	-0.0216	-0.0031
	[0.0033]	[0.0059]	[0.0029]	[0.0014]
	0.4639	0.1953	0.2820	0.0588

Notes: The Emergency Department visits used to estimate the regressions are a near census of ED visits in Arizona (2005-2007), California (2005-2007), Iowa (2004-2007), New Jersey (2004-2007) and Wisconsin (2004-2007).The parameter estimates in the table above are the percentage point change in insurance coverage when people age out of their insurance coverage on the last day of the month in which they turn 19. The standard errors are in brackets directly below the parameter estimates. Below the SE we have included the estimated level of the dependant variable immediately before people age out. The parameter estimates are adjusted for the decline in admissions under the assumption that the decline in admission is due entirely to people losing their insurance coverage. The adjustment is made by estimating the insurance coverage regression and the log(admissions) then using the estimated percent drop in admissions to adjust the coverage estimates. The regressions are run on the averages for one month cells as this is the most refined version of the age variable available. The regressions include all individuals 18 to 20 that appear in the Emergency Department records. There are 1,789,954 admissions in this age range, of these 1,025,554 are for females, 712,904 are male and the remainder are of unknown gender.

Table 5: Change at Age 19 in Volume of Emergency Department Visits

	All Visits	Public Hospitals	Non Profit Hospitals	For Profit Hospitals
	(1)	(2)	(3)	(4)
All	-0.0333	-0.0058	-0.0375	-0.0438
	[0.0060]	[0.0102]	[0.0064]	[0.0102]
All (Except Pregnant)	-0.0351	-0.0094	-0.0385	-0.0471
	[0.0061]	[0.0112]	[0.0063]	[0.0112]
Male	-0.0329	0.0076	-0.039	-0.0505
	[0.0056]	[0.0135]	[0.0054]	[0.0138]
Female	-0.033	-0.017	-0.0353	-0.0404
	[0.0080]	[0.0143]	[0.0084]	[0.0132]
Female Not Pregnant	-0.036	-0.0264	-0.0366	-0.0457
	[0.0080]	[0.0166]	[0.0085]	[0.0154]

Notes: See notes from Table 4. The dependent variable in all the regressions above is the log of admissions at each age in months. Of the 1,789,954 total visits among people age 18 and 19: 263,524 are to public hospitals, 1,310,168 are to non profits, 193,023 are to for profit hospitals and the remaining admissions are to hospitals of unknown ownership type.

Table 6: Impact of Losing Insurance Coverage on Emergency Department Visits

	All Visits	Public Hospitals	Non Profit Hospitals	For Profit Hospitals
	(1)	(2)	(3)	(4)
All	-0.4041 [0.0776]	-0.0709 [0.1259]	-0.4539 [0.0832]	-0.5292 [0.1296]
All (Except Pregnant)	-0.4094 [0.0762]	-0.1110 [0.1332]	-0.4490 [0.0792]	-0.5468 [0.1368]
Male	-0.3889 [0.0714]	0.0915 [0.1625]	-0.4601 [0.0708]	-0.5926 [0.1700]
Female	-0.4099 [0.1053]	-0.2127 [0.1814]	-0.4380 [0.1108]	-0.5009 [0.1707]
Female Not Pregnant	-0.4191 [0.0994]	-0.3088 [0.1979]	-0.4261 [0.1052]	-0.5295 [0.1864]

Notes: See notes from Table 5. The estimates above are the ratio of the change in admissions to the overall change in insurance coverage. The standard errors are in brackets below the estimates. The ratios and their standard errors are computed by estimating the relevant regressions via seemingly unrelated regression.

Table 7: Change at 19 in Insurance Coverage of People Admitted to the Hospital

	Private	Uninsured	Medicaid	Other Insurance
	(1)	(2)	(3)	(4)
All	-0.0458	0.0271	0.0187	0.0005
	[0.0027]	[0.0052]	[0.0032]	[0.0005]
	0.3392	0.0762	0.5396	0.0420
Male	-0.0691	0.0626	0.0072	0.0010
	[0.0043]	[0.0049]	[0.0034]	[0.0013]
	0.4888	0.1313	0.2896	0.0849
Female not Pregnant	-0.0621	0.0496	0.0121	0.0016
	[0.0043]	[0.0075]	[0.0044]	[0.0015]
	0.5137	0.0993	0.3266	0.0543
Female Pregnant	-0.0332	0.0091	0.0239	0.0001
	[0.0029]	[0.0078]	[0.0056]	[0.0005]
	0.2311	0.0476	0.6986	0.0217

Notes: The estimates above are from a near census of hospital stays in Arizona (2000-2007), California (1990-2006), Iowa (2004-2007), New York (1990-2006), Texas (1999-2003) and Wisconsin (2004-2007). Combining the data from the six states gives a sample of 849,610 18 and 19 year olds. This table presents estimates of the change in insurance coverage (among people admitted to the hospital) that occurs on the first day of the month after people turn 19. Directly below the estimates are the standard errors of the estimates and below the standard errors are the proportion of the population with this type of coverage immediately before people age out at 19. The estimates are made using a linear polynomial in age for estimated using admissions among people age 18 to age 20. The estimates of the change in insurance are adjusted for the effect of insurance status on the probability of getting treated.

Table 8: Change at Age 19 in Admissions to the Hospital

	All Visits	Via Emergency Department	Not Via Emergency Department
	(1)	(2)	(3)
All	-0.0168	-0.0096	-0.0202
	[0.0057]	[0.0057]	[0.0082]
Male	-0.0386	-0.0195	-0.0670
	[0.0057]	[0.0075]	[0.0114]
Female not Pregnant	-0.0333	-0.0125	-0.0602
	[0.0086]	[0.0123]	[0.0089]
Female Pregnant	-0.0053	0.0116	-0.0079
	[0.0086]	[0.0099]	[0.0091]
Public	0.0026	0.0181	-0.0122
	[0.0069]	[0.0087]	[0.0117]
Private Non Profit	-0.0145	-0.0192	-0.0127
	[0.0060]	[0.0074]	[0.0087]
Private For Profit	-0.0394	-0.0342	-0.0405
	[0.0104]	[0.0189]	[0.0117]

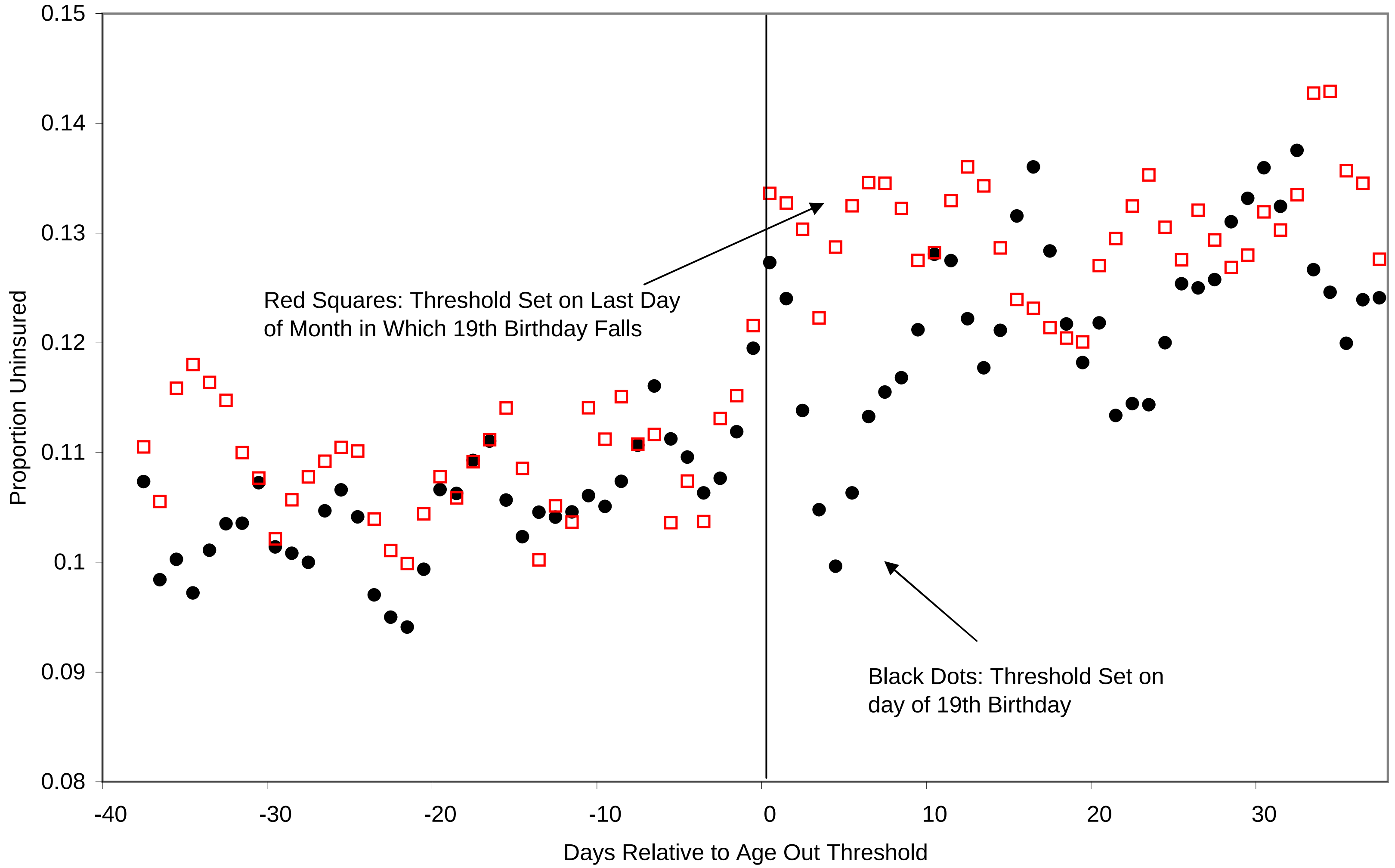
Notes: See notes from Table 7. The dependant variable is the log of admissions and the results are for overall admissions and split by route into the hospital

Table 9: Impact of Losing Insurance on Admissions to the Hospital

	All Visits	Via Emergency Department	Not Via Emergency Department
	(1)	(2)	(3)
All	-0.6135	-0.3509	-0.7376
	[0.2414]	[0.2208]	[0.3343]
Male	-0.6052	-0.3087	-1.0352
	[0.1030]	[0.1222]	[0.2004]
Female not Pregnant	-0.6599	-0.2503	-1.1791
	[0.2010]	[0.2510]	[0.2569]
Female Pregnant	-0.5853	1.2829	-0.8668
	[1.0731]	[1.5496]	[1.2521]
Public	0.0951	0.6722	-0.4464
	[0.2550]	[0.3453]	[0.4399]
Private Non Profit	-0.5295	-0.7021	-0.4650
	[0.2438]	[0.3047]	[0.3331]
Private For Profit	-1.4241	-1.2409	-1.4629
	[0.4739]	[0.7376]	[0.5177]

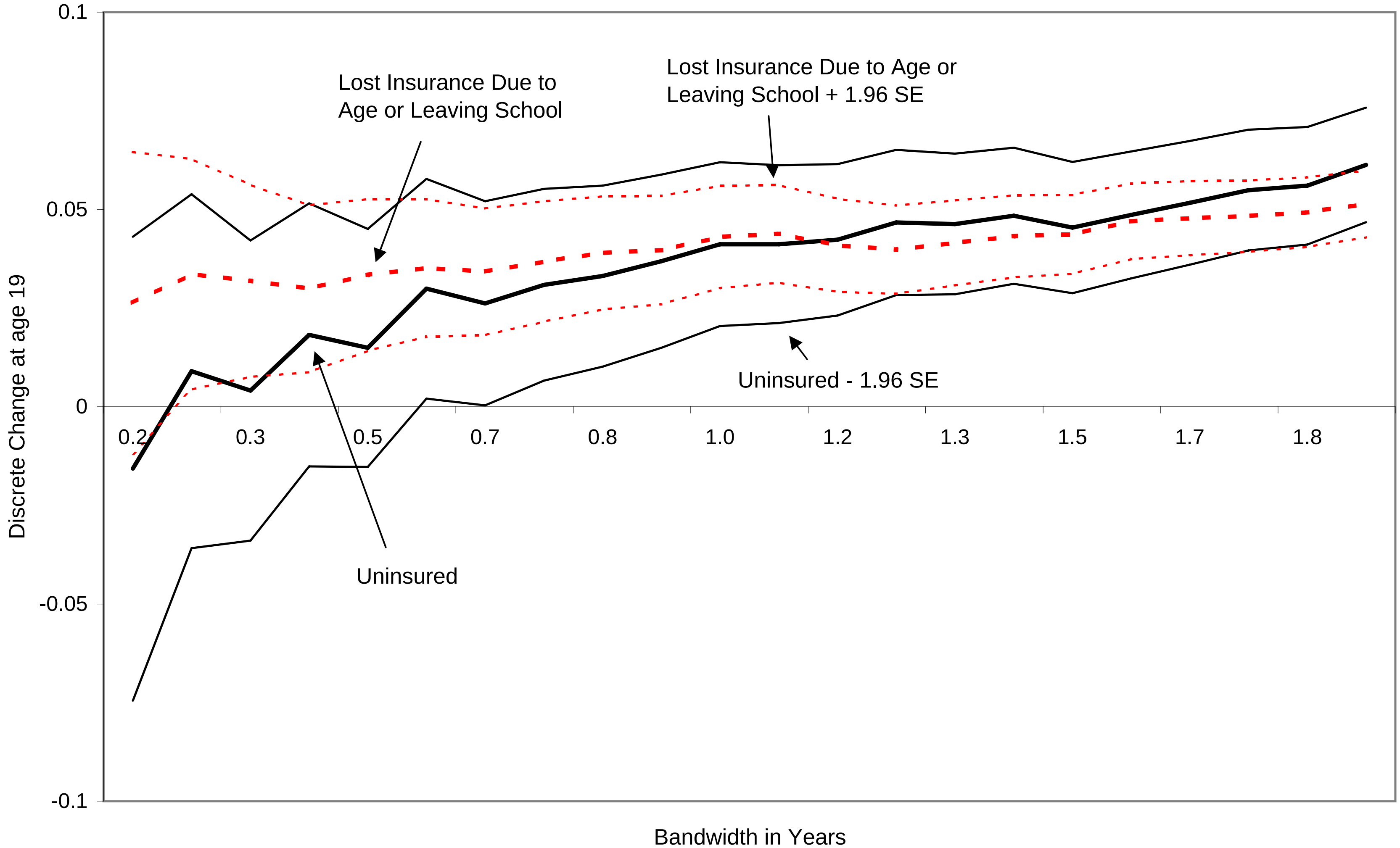
Notes: See notes from Table 8. The elasticities above are the impact of losing insurance on hospital admissions. They are computed by dividing the percent change in admissions by the percent change in the population that is uninsured.

Appendix 1: Comparing Two Possible Ways of Setting Age Out Threshold



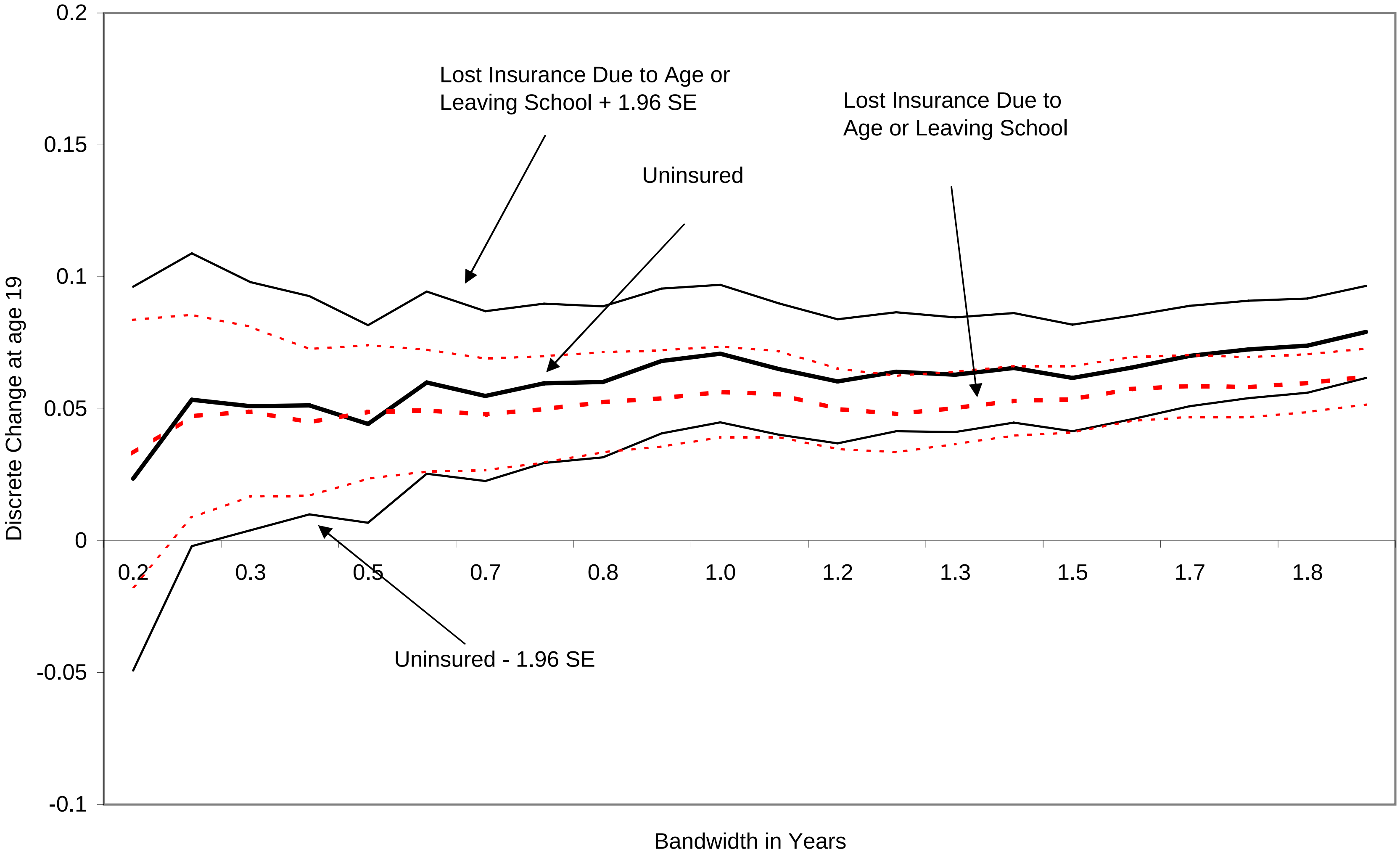
Notes: Estimates are for non pregnant hospital discharges in the California data.

Appendix 2: Assessing Sensitivity of Estimate of Change in Insurance to Bandwidth Choice



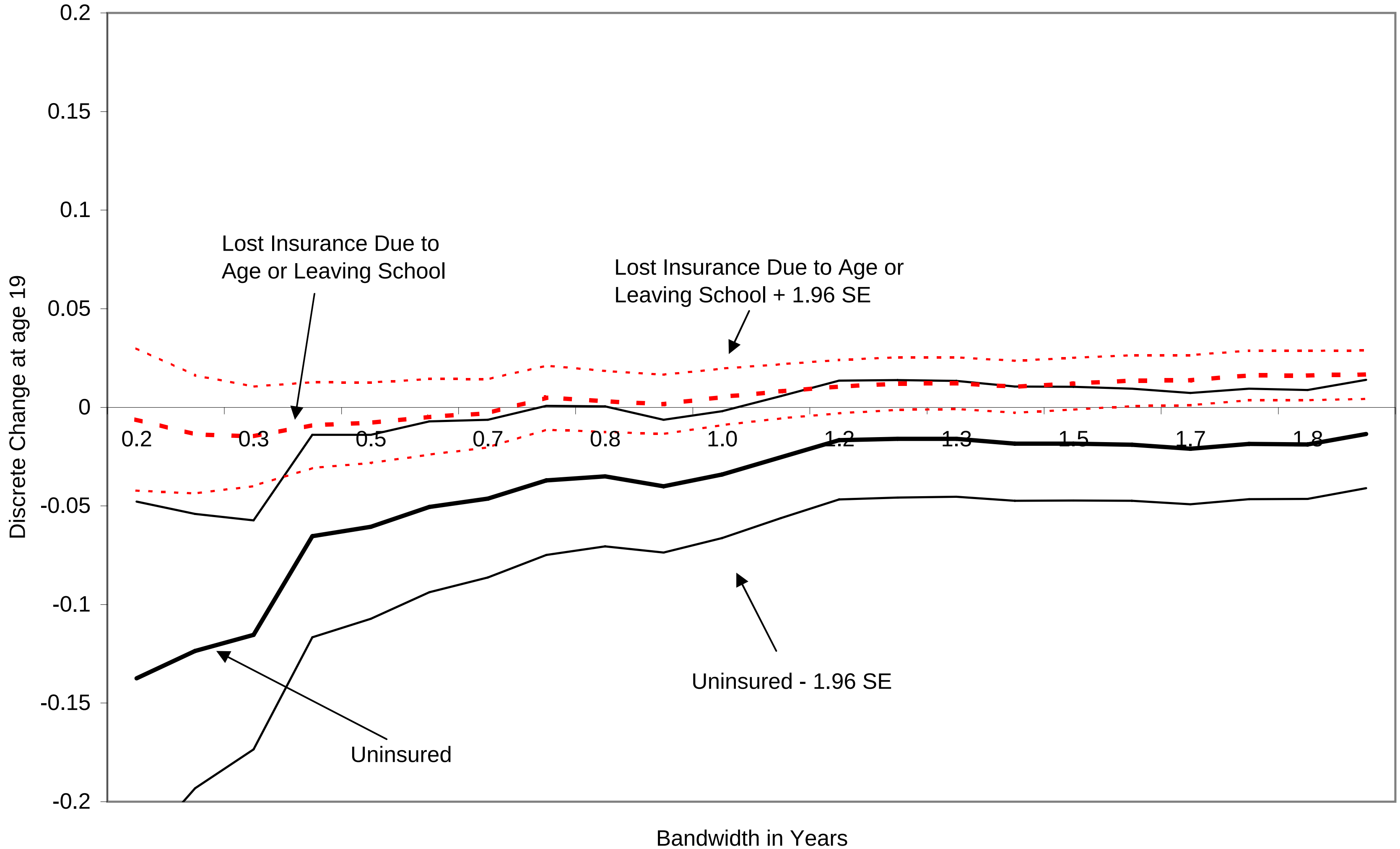
Notes: The estimates above are the discrete change at age 19 from a local linear regression with a symmetric bandwidth. The heavy line is the point estimate and the lighter lines are the confidence intervals.

Appendix 3: Assessing Sensitivity of Estimate of Change in Insurance to Bandwidth Choice
People Not Attending School



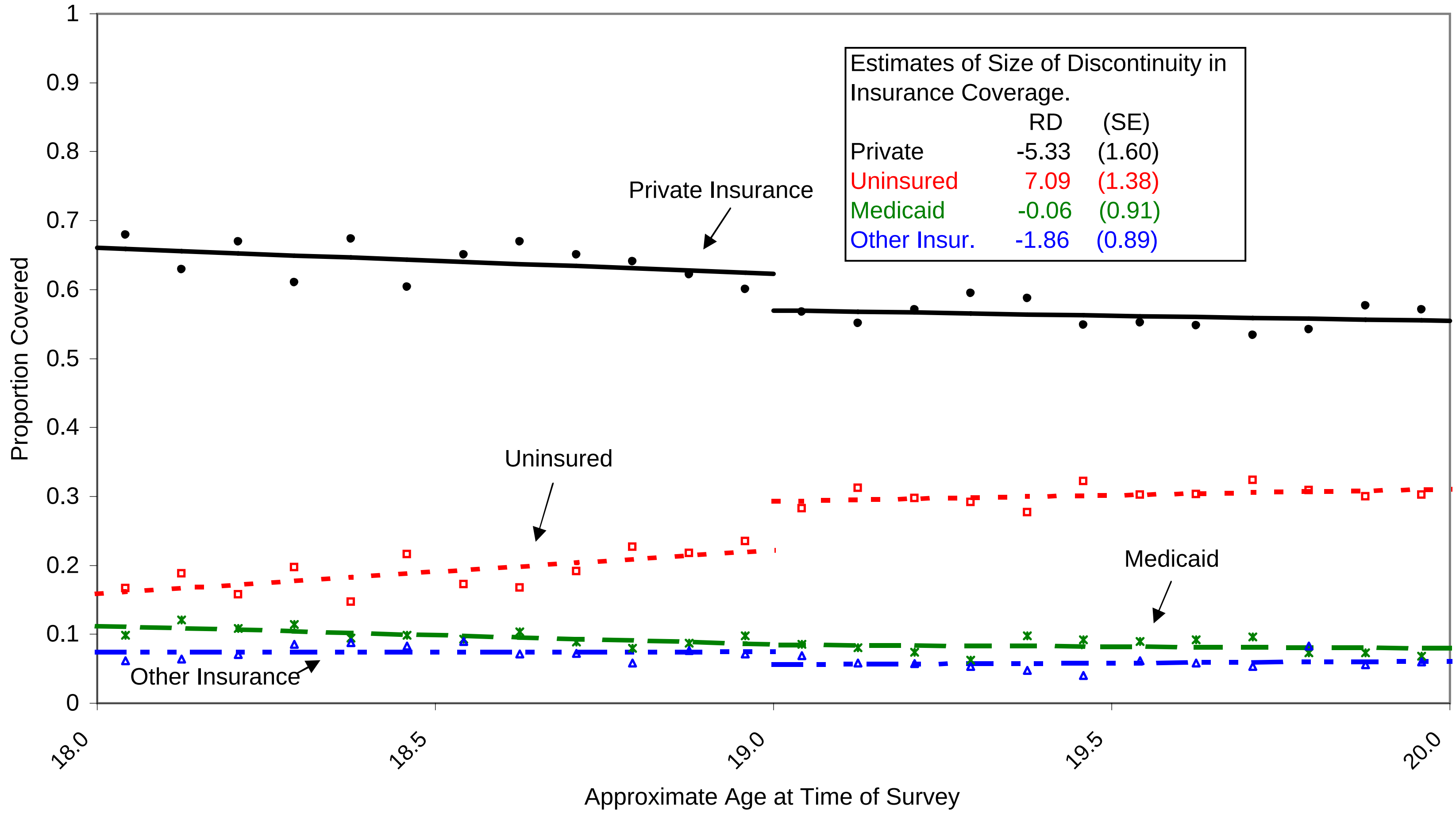
Notes: The estimates above are the discrete change at age 19 from a local linear regression with a symmetric bandwidth. The heavy line is the point estimate and the lighter lines are the confidence intervals.

Appendix 4: Assessing Sensitivity of Estimate of Change in Insurance to Bandwidth Choice
People Attending School



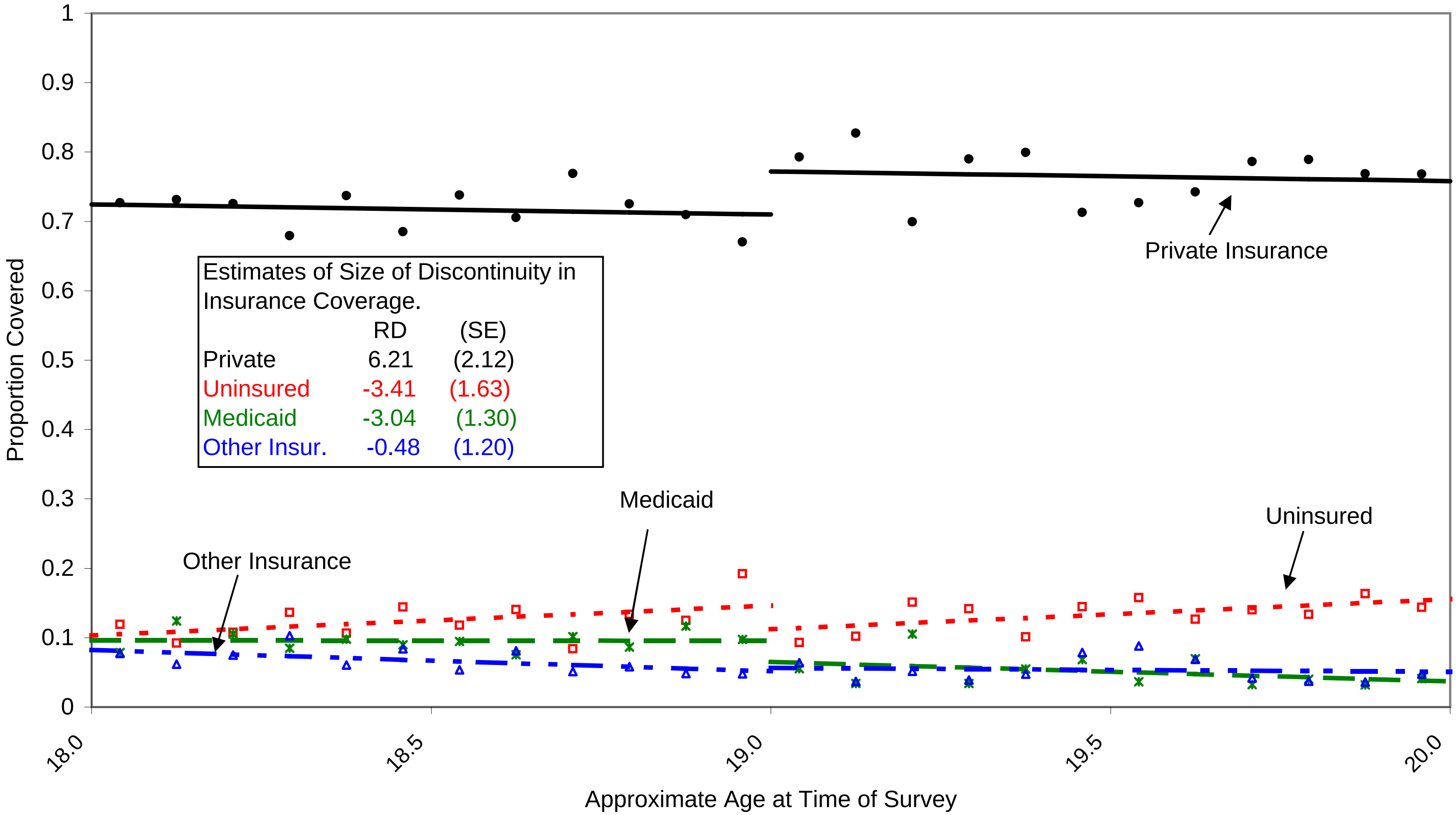
Notes: The estimates above are the discrete change at age 19 from a local linear regression with a symmetric bandwidth. The heavy line is the point estimate and the lighter lines are the confidence intervals.

Appendix 5: Age Profile of Health Insurance Coverage in the United States
Not in School



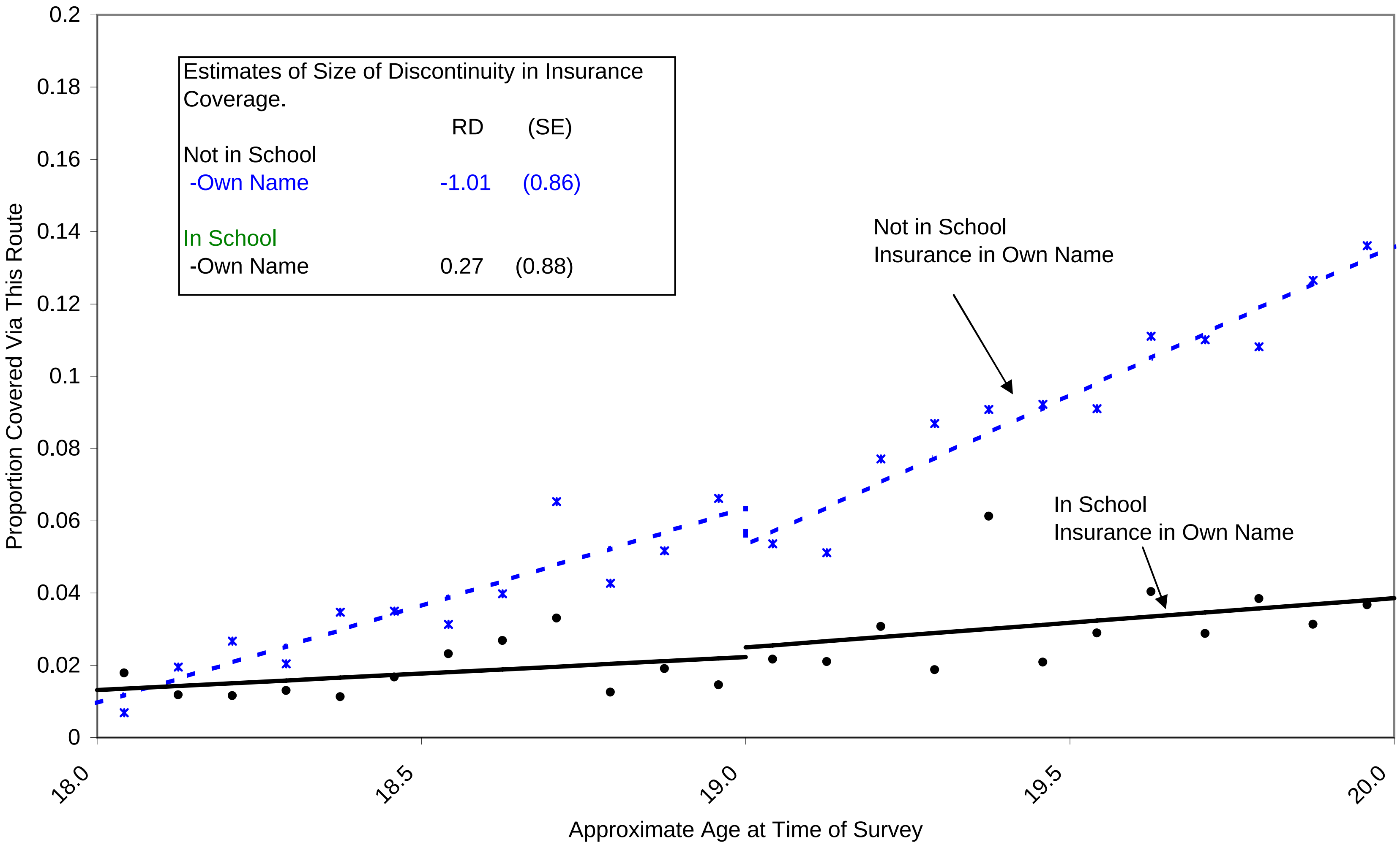
Notes: Regressions and proportions are weighted to take into account the stratified structure of the NHIS. The regression lines superimposed on the proportions are from a linear polyn in age interacted with a dummy that takes on a value of one for people over 19 and 0 otherwise. This regression is fit on the micro data rather than the means of the bins. The age variable is centered on the last day of the month on which the individual's 19th birthday falls. Individuals with unknown month of birth comprise 11.1 percent of the surveyed population that are 18 at the time of the survey and they have been dropped from the analysis. The age profiles above include 17,058 individuals from the NHIS person files.

Appendix 6: Age Profile of Health Insurance Coverage in the United States
In School



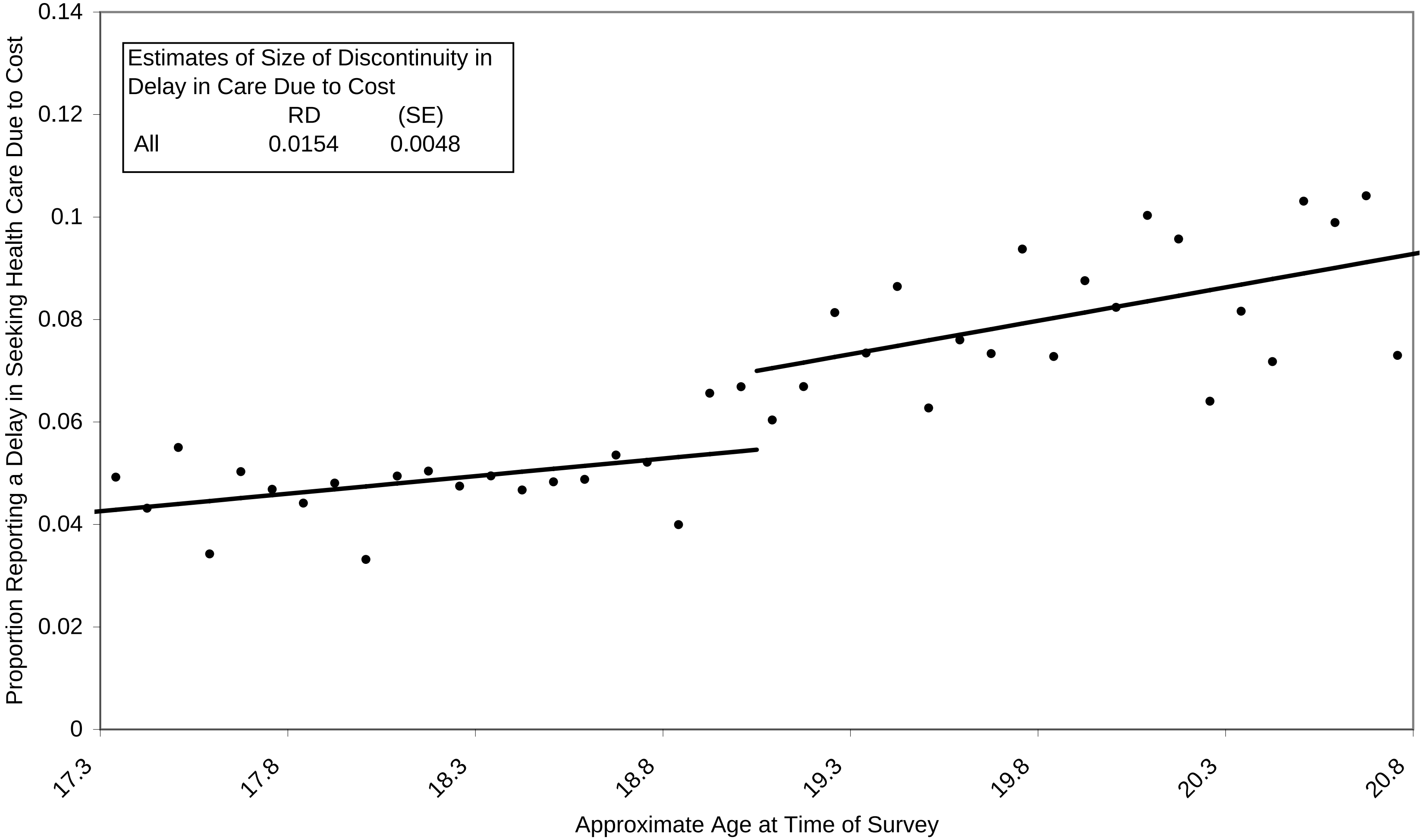
Notes: Regressions and proportions are weighted to take into account the stratified structure of the NHIS. The regression lines superimposed on the proportions are from a linear polynomial in age interacted with a dummy that takes on a value of one for people over 19 and 0 otherwise. This regression is fit on the micro data rather than the means of the bins. The age variable is centered on the last day of the month on which the individual's 19th birthday falls. Individuals with unknown month of birth comprise 11.1 percent of the surveyed population that are 18 or 19 at the time of the survey and they have been dropped from the analysis. The age profiles above include 7,202 individuals from the NHIS person files.

Appendix 7: Age Profile of Source of Insurance Coverage by School Attendance



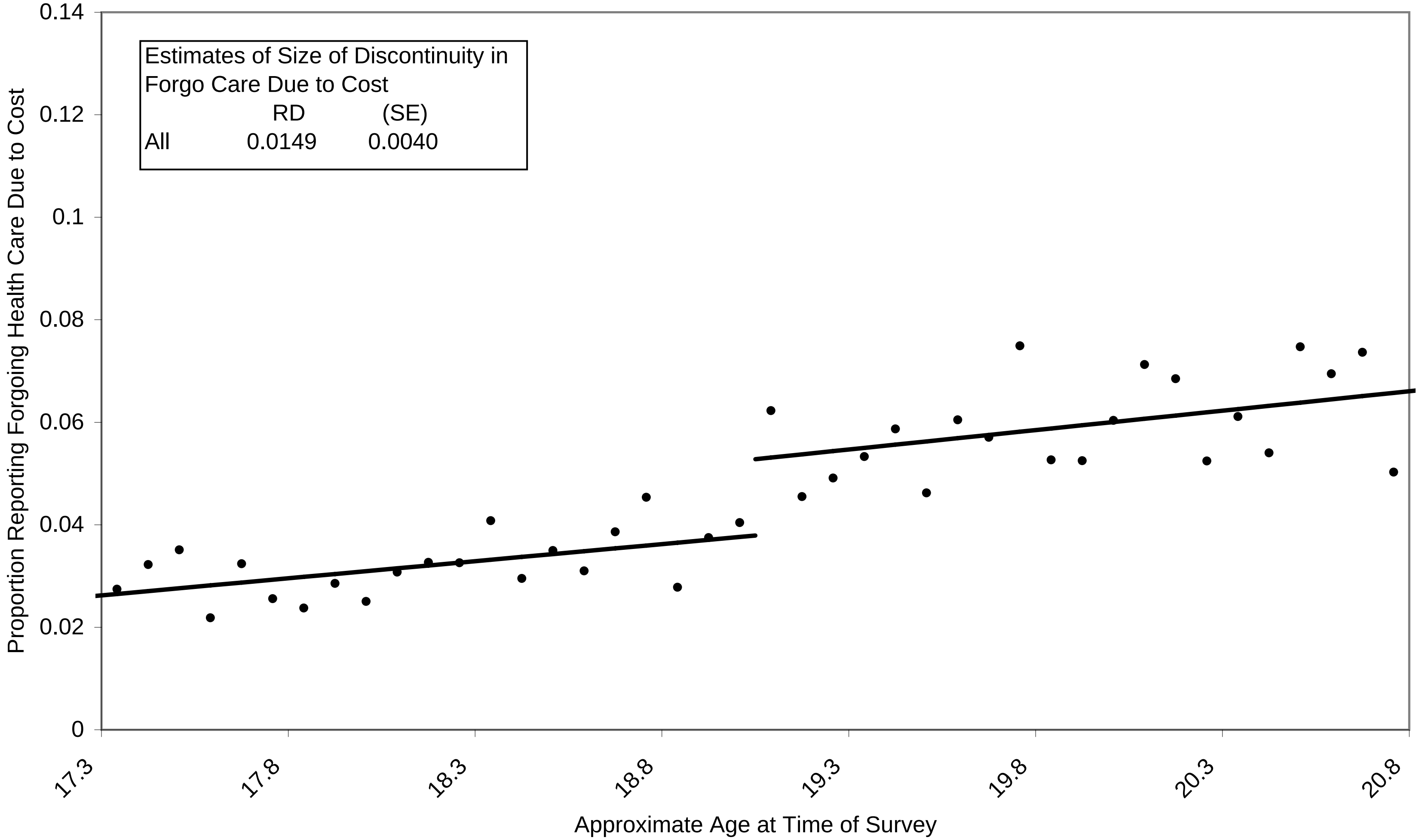
Notes: See notes from Appendix 6.

Appendix 8: Age Profile of Delay in Care Due to Cost
National Health Interview Survey (1997-2007)



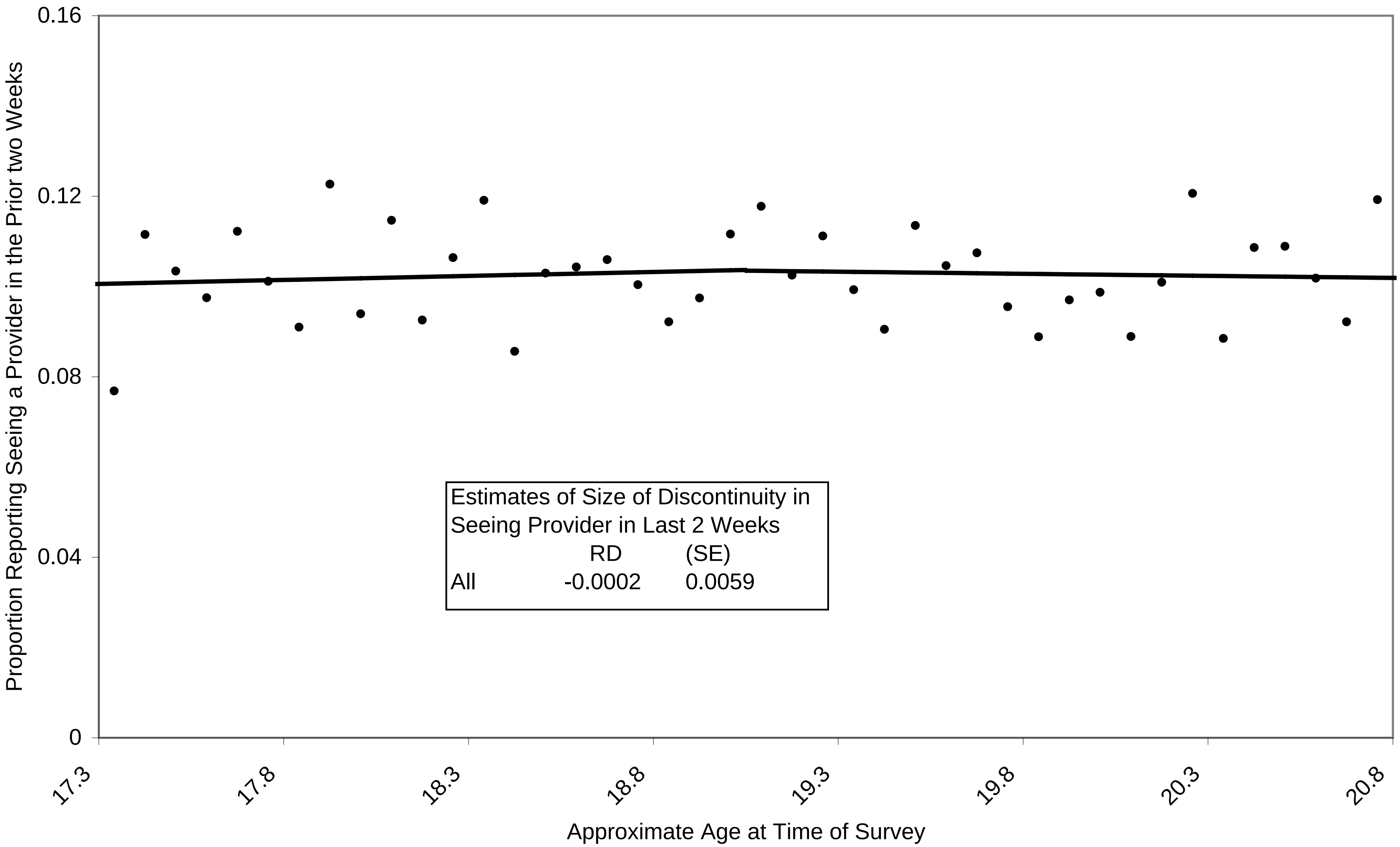
Notes: See notes from Figure 2. The question used to construct the age profiles in this figure reads as follows. "During the past 12 months, has medical care been delayed for {person} because of worry about the cost? (Do not include dental care)."

Appendix 9: Age Profile of Forging Care Due to Cost
National Health Interview Survey (1997-2007)



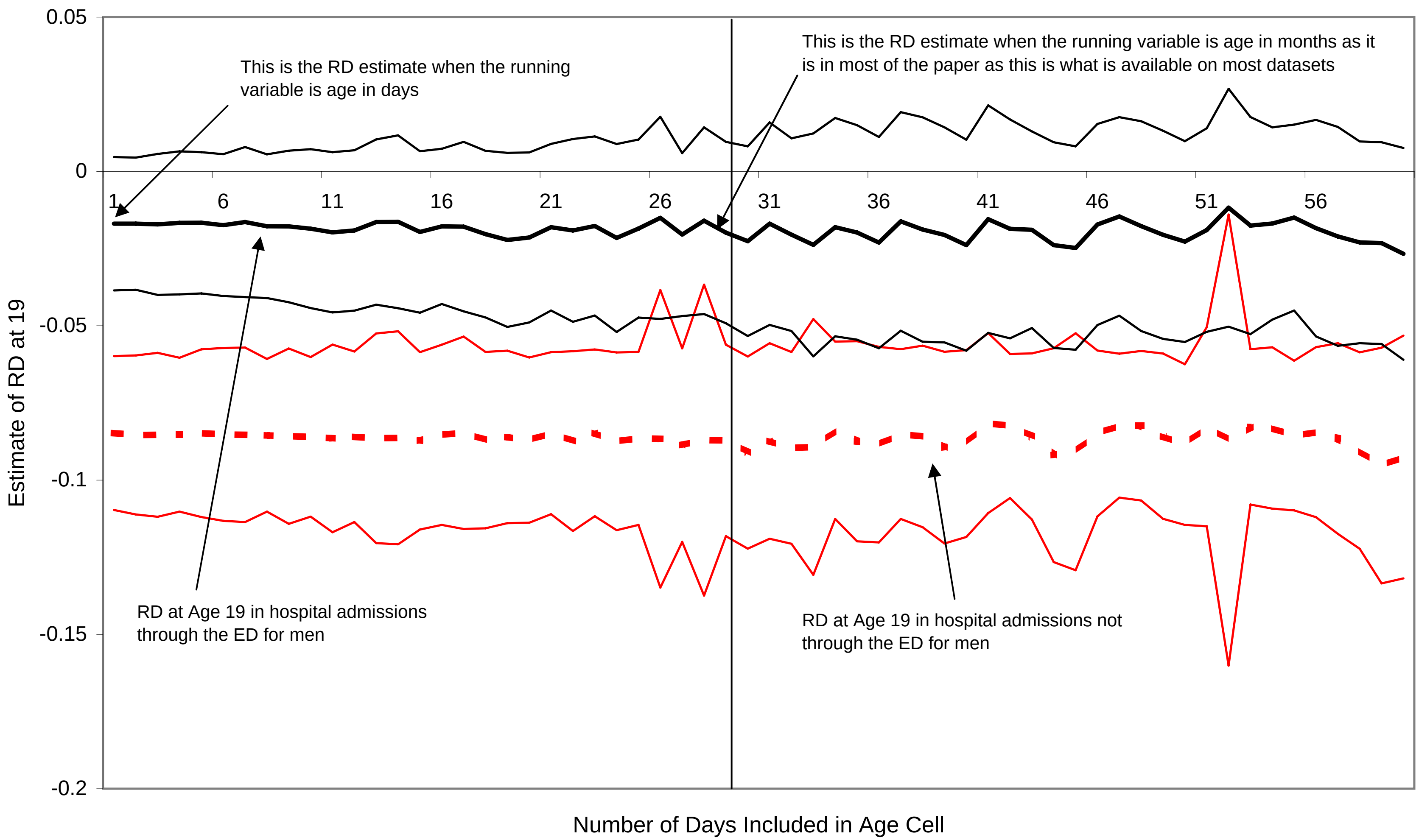
Notes: See notes from Figure 2. The question used to construct the age profiles in this figure reads as follows. "During the past 12 months, was there any time when {person} needed medical care, but did not get it because {person} couldn't afford it?"

Appendix 10: Age Profile of See Provider in Last Two Weeks
National Health Interview Survey (1997-2007)



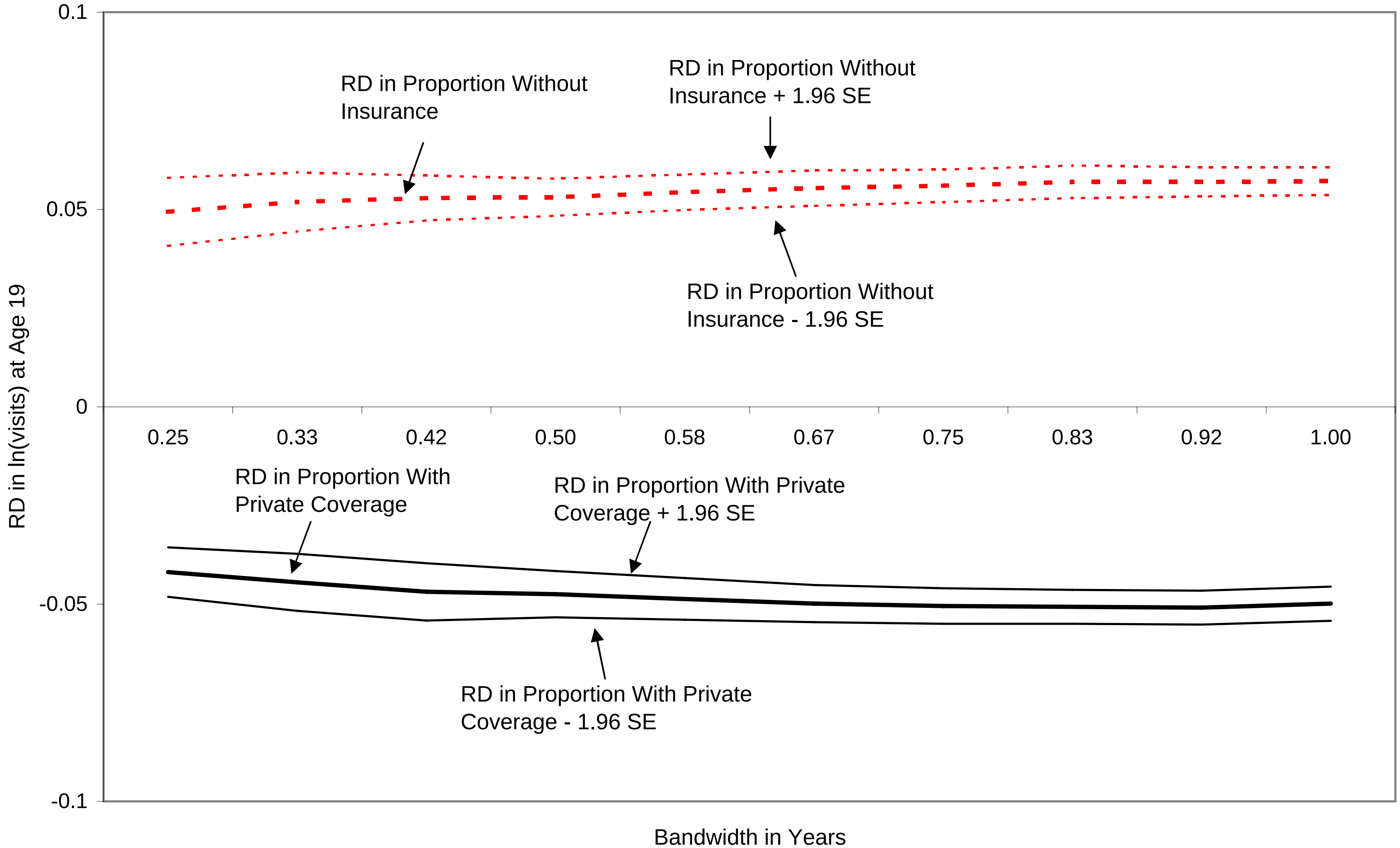
Notes: See notes from Figure 2. The question used to construct the age profiles in this figure reads as follows. "During those 2 weeks, did {person} see a doctor or other health care professional at a doctor's office, a clinic, an emergency room, or some other place? (do no include times during an overnight hospital stay)"

Appendix 11: Impact on RD Estimates of Coarsening the Age Variable from Age in Days to 60 Day Cells



Notes: The regressions in the paper all have age cells of approximately 30 because age is typically only available in months. The heavy lines are the estimates of the RD and the lighter lines are the confidence intervals.

Appendix 12: Assessing Sensitivity to Bandwidth Choice of Estimate of Change in Insurance Among People Treated in the Emergency Department



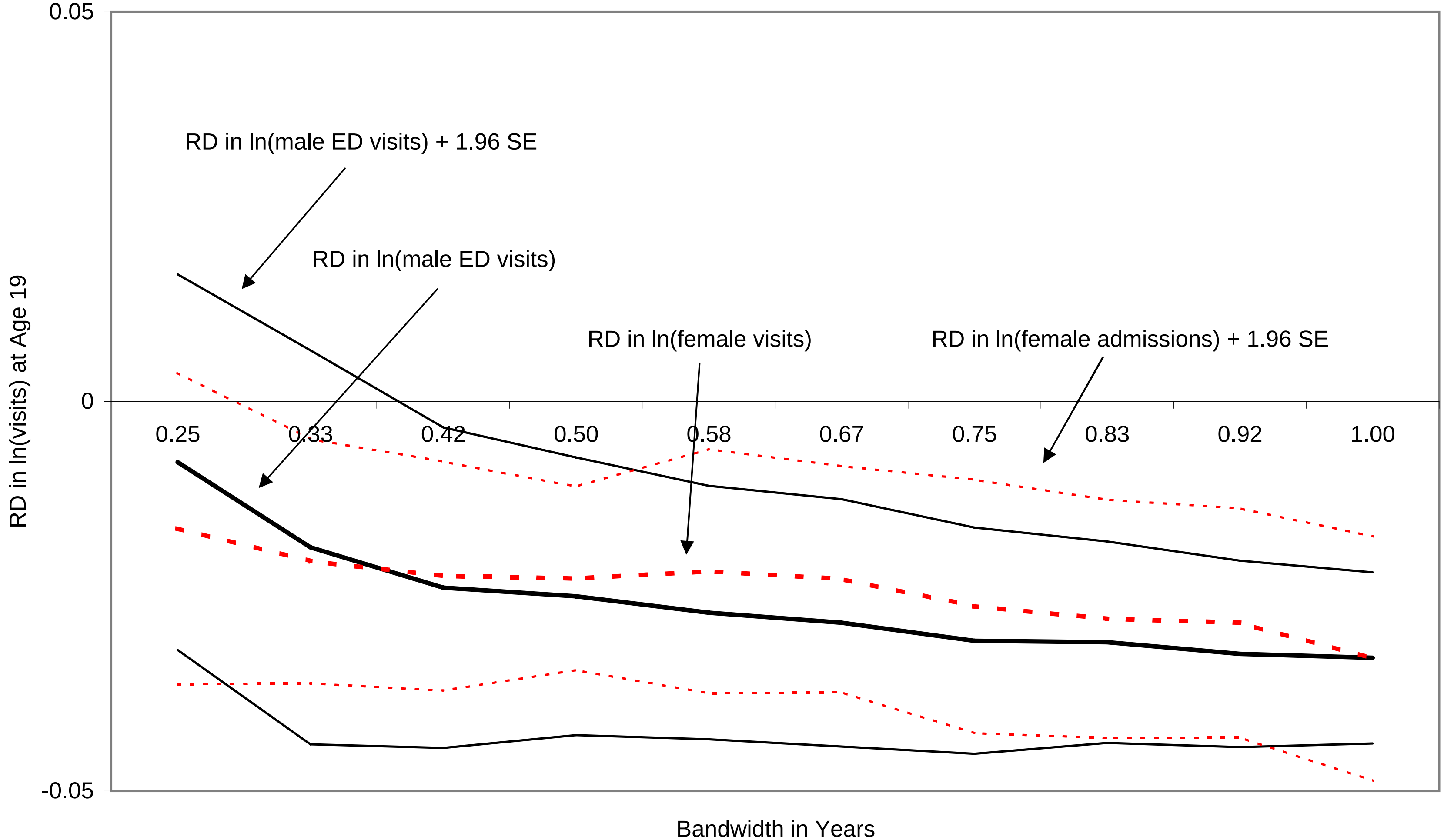
Notes: The estimates above are the discrete change at age 19 from a local linear regression with a symmetric bandwidth. The heavy line is the point estimate and the lighter lines are the confidence intervals.

Appendix 13: Change at Age 19 in Insurance Coverage of Emergency Department Visits by State

	Private	Uninsured	Medicaid	Other Insurance
	(1)	(2)	(3)	(4)
All States	-0.0628	0.0810	-0.0166	-0.0015
	[0.0026]	[0.0046]	[0.0024]	[0.0010]
	0.4471	0.2154	0.2644	0.0731
Arizona	-0.0437	0.0537	-0.0052	-0.0048
	[0.0053]	[0.0108]	[0.0064]	[0.0031]
	0.3462	0.2144	0.3519	0.0874
California	-0.0659	0.0760	-0.0059	-0.0042
	[0.0036]	[0.0057]	[0.0029]	[0.0017]
	0.4073	0.2141	0.2944	0.0842
Iowa	-0.0514	0.0740	-0.0209	-0.0017
	[0.0072]	[0.0105]	[0.0059]	[0.0027]
	0.4935	0.1818	0.2654	0.0593
New Jersey	-0.0722	0.0851	-0.0144	0.0015
	[0.0038]	[0.0044]	[0.0029]	[0.0011]
	0.5637	0.2751	0.1180	0.0431
Wisconsin	-0.0613	0.1331	-0.0799	0.0081
	[0.0068]	[0.0100]	[0.0060]	[0.0027]
	0.4937	0.1490	0.2872	0.0701

Notes: The Emergency Department visits used to estimate the regressions are a near census of ED visits in Arizona (2005-2007), California (2005-2007), Iowa (2004-2007), New Jersey (2004-2007) and Wisconsin (2004-2007).The parameter estimates in the table above are the percentage point change in insurance coverage when people age out of their insurance coverage on the last day of the month in which they turn 19. The standard errors are in brackets directly below the parameter estimates. Below the SE we have included the estimated level of the dependant variable immediately before people age out. The parameter estimates are adjusted for the decline in admissions under the assumption that the decline in admission is due entirely to people losing their insurance coverage. The adjustment is made by estimating the insurance coverage regression and the log(admissions) regressions via seemingly unrelated regression.

Appendix 14: Assessing Sensitivity to Bandwidth Choice of Estimate of Change in Number of People Treated in the Emergency Department



Notes: The estimates above are the discrete change at age 19 from a local linear regression with a symmetric bandwidth. The heavy line is the point estimate and the lighter lines are the confidence intervals.

Appendix 15: Change at Age 19 in Volume of Emergency Department Visits by State

	All Visits	Public Hospitals	Non Profit Hospitals	For Profit Hospitals
	(1)	(2)	(3)	(4)
All	-0.0333	-0.0058	-0.0375	-0.0438
	[0.0060]	[0.0102]	[0.0064]	[0.0102]
Arizona	-0.0287	0.0006	-0.0283	-0.0427
	[0.0132]	[0.0325]	[0.0155]	[0.0212]
California	-0.0368	-0.0012	-0.0463	-0.0473
	[0.0074]	[0.0107]	[0.0089]	[0.0101]
Iowa	-0.0444	-0.0295	-0.0502	N/A
	[0.0136]	[0.0267]	[0.0148]	N/A
New Jersey	-0.0164	-0.0013	-0.0177	0.0729
	[0.0080]	[0.0354]	[0.0087]	[0.0645]
Wisconsin	-0.0464	0.0210	-0.0493	0.0823
	[0.0126]	[0.0867]	[0.0126]	[0.0646]

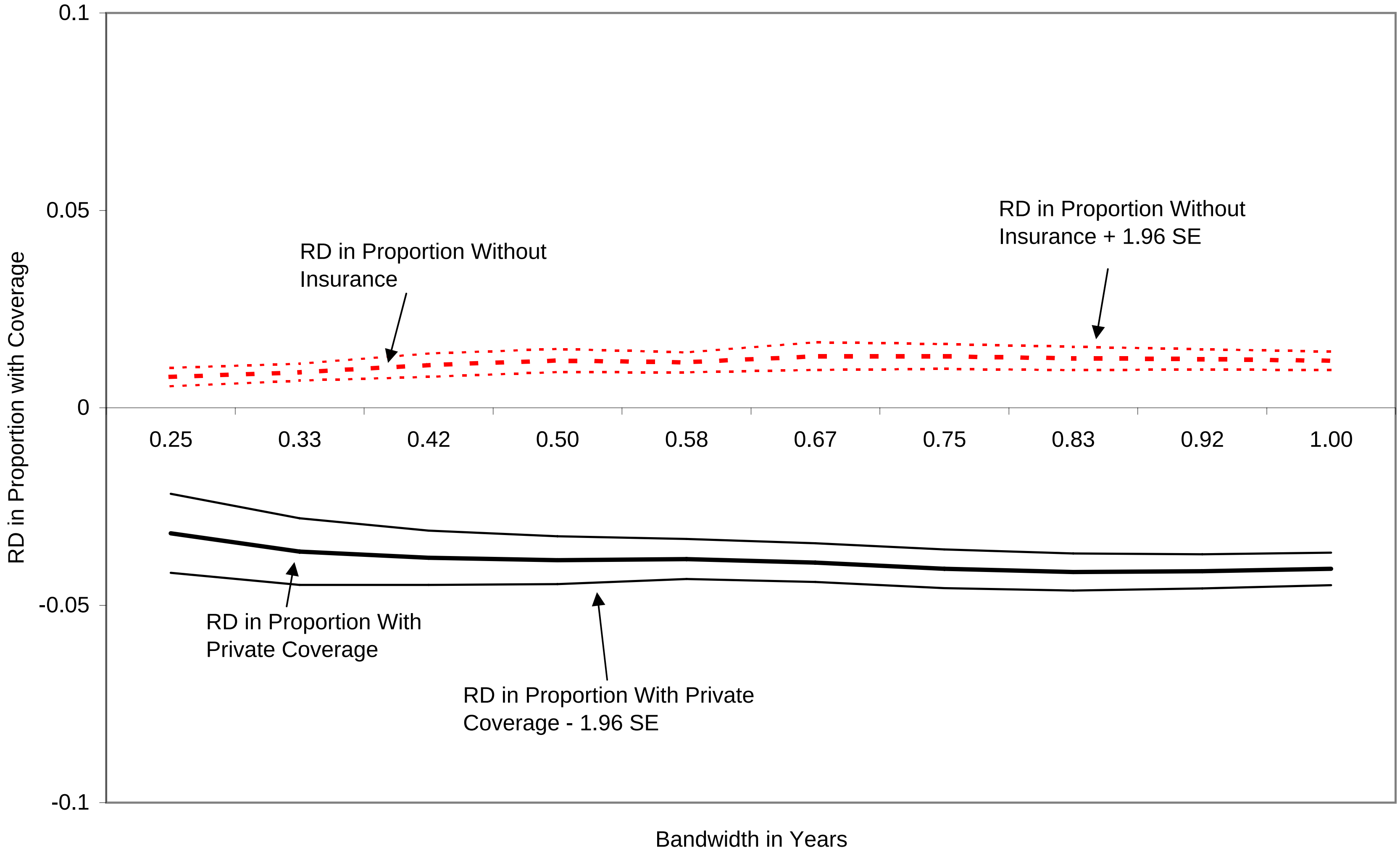
Notes: See notes from Appendix 13. The dependent variable in all the regressions above is the log of admissions at each age in months. Of the 1,789,954 total visits among people age 18 and 19: 263,524 are to public hospitals, 1,310,168 are to non profits, 193,023 are to for profit hospitals and the remaining admissions are to hospitals of unknown ownership type. In the HCUP data there are no hospitals coded as private in Iowa.

Appendix 16: Estimates of Impact of Losing Insurance Coverage on Emergency Department Visits by State

	All Admissions	Public Hospitals	Non Profit Hospitals	For Profit Hospitals
	(1)	(2)	(3)	(4)
All	-0.4041	-0.0709	-0.4539	-0.5292
	[0.0776]	[0.1259]	[0.0832]	[0.1296]
Arizona	-0.5267	0.0106	-0.5197	-0.7773
	[0.2681]	[0.6049]	[0.3073]	[0.4257]
California	-0.4755	-0.0163	-0.5954	-0.6074
	[0.1038]	[0.1407]	[0.1256]	[0.1408]
Iowa	-0.5862	-0.3931	-0.6616	N/A
	[0.2024]	[0.3650]	[0.2218]	N/A
New Jersey	-0.1908	-0.0147	-0.2065	0.8880
	[0.0945]	[0.4159]	[0.1027]	[0.7591]
Wisconsin	-0.3407	0.1594	-0.3616	0.6446
	[0.0982]	[0.6516]	[0.0987]	[0.4877]

Notes: See notes from Appendix 14. The estimates above are the ratio of the change in admissions to the overall change in insurance coverage. The standard errors are in brackets below the estimates. The ratios and their standard errors are computed by estimating the relevant regressions via seemingly unrelated regression. In the HCUP data there are no hospitals coded as private in Iowa.

Appendix 17: Assessing Sensitivity to Bandwidth Choice of Estimate of Change in Insurance Among People Admitted to the Hospital



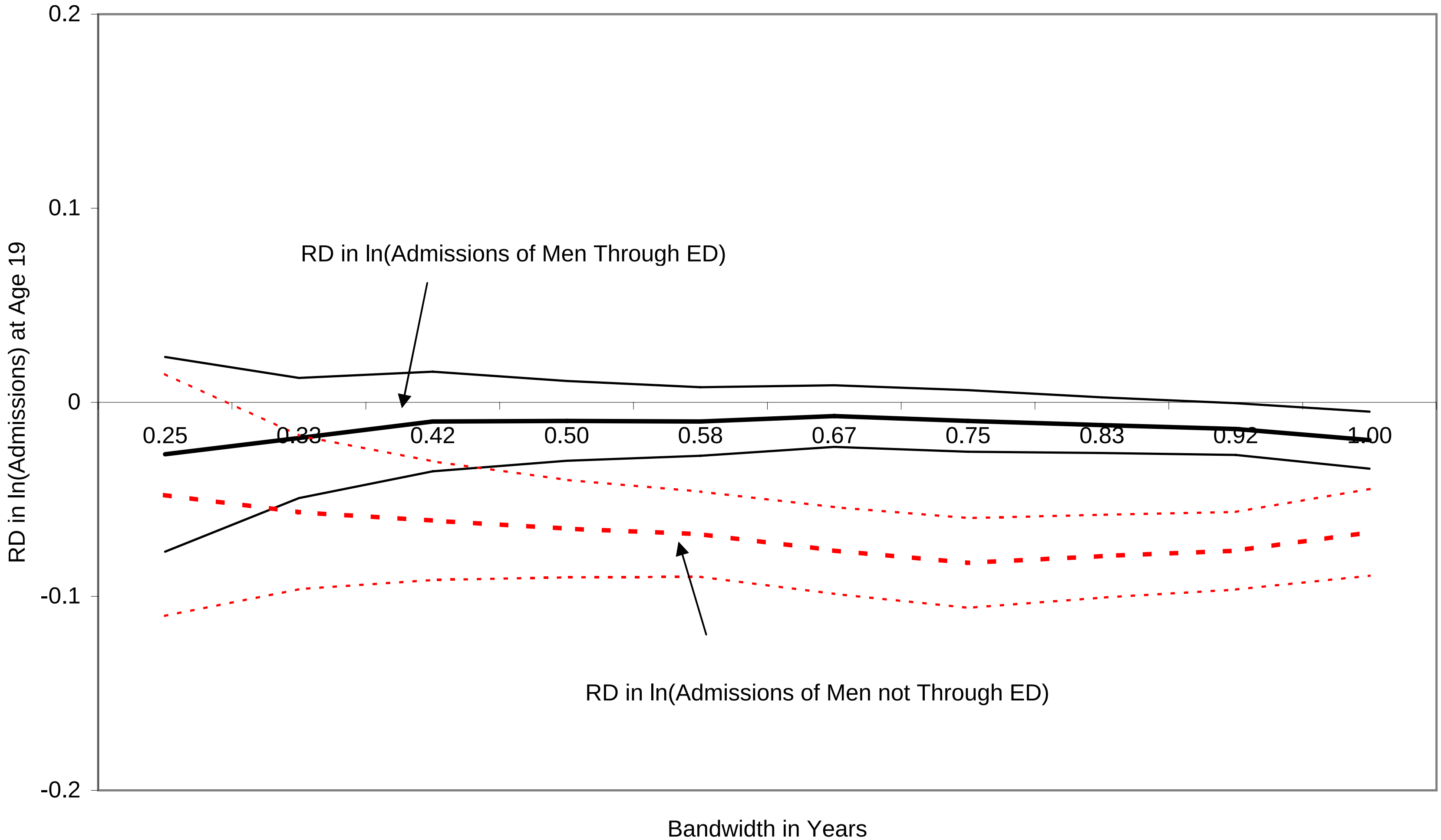
Notes: The estimates above are the discrete change at age 19 from a local linear regression with a symmetric bandwidth. The heavy line is the point estimate and the lighter lines are the confidence intervals.

Appendix 18: Change at 19 in Insurance Coverage of People Admitted to the Hospital by State

	Private	Uninsured	Medicaid	Other Insurance
	(1)	(2)	(3)	(4)
All	-0.0458	0.0271	0.0187	0.0005
	[0.0027]	[0.0052]	[0.0032]	[0.0005]
	0.3392	0.0762	0.5396	0.0420
Arizona	-0.0409	0.0294	0.0091	0.0031
	[0.0070]	[0.0102]	[0.0081]	[0.0028]
	0.3090	0.0436	0.5704	0.0724
California	-0.0439	0.0272	0.0168	0.0004
	[0.0029]	[0.0057]	[0.0034]	[0.0007]
	0.3309	0.0660	0.5638	0.0368
Iowa	-0.0402	-0.0192	0.0651	-0.0059
	[0.0231]	[0.0254]	[0.0208]	[0.0048]
	0.4103	0.0537	0.5037	0.0325
New York	-0.0599	0.0256	0.0353	-0.0003
	[0.0038]	[0.0059]	[0.0045]	[0.0012]
	0.3837	0.0985	0.4846	0.0296
Texas	-0.0234	0.0252	-0.0014	-0.0003
	[0.0042]	[0.0089]	[0.0071]	[0.0021]
	0.2787	0.0960	0.5436	0.0787
Wisconsin	-0.0856	0.0830	-0.0142	0.0184
	[0.0087]	[0.0167]	[0.0147]	[0.0061]
	0.4774	0.0497	0.4342	0.0370

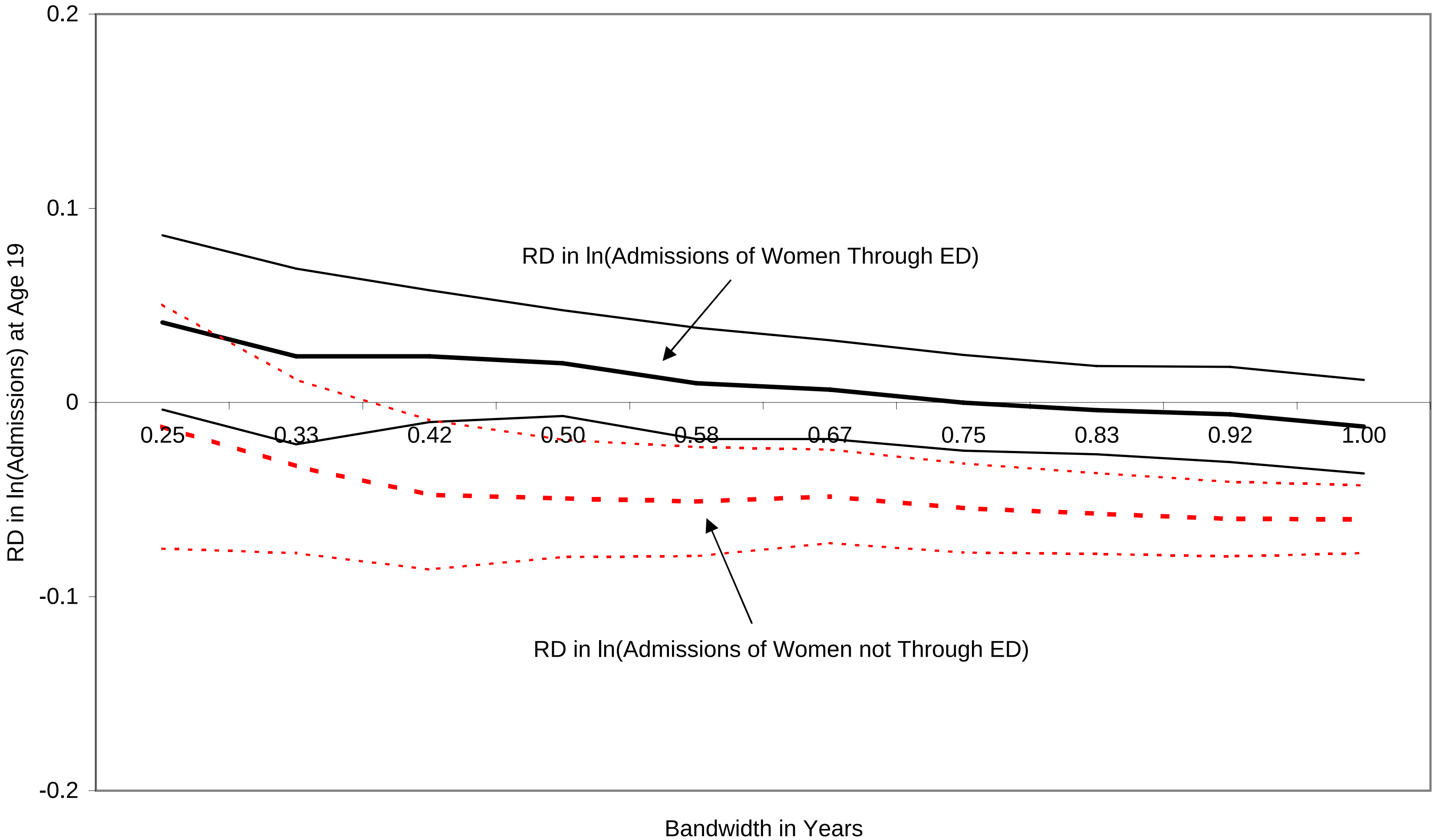
Notes: The estimates above are from a near census of hospital stays in Arizona (2000-2007), California (1990-2006), Iowa (2004-2007), New York (1990-2006), Texas (1999-2003) and Wisconsin (2004-2007). Combining the data from the six states gives a sample of 849,610 18 and 19 year olds. This table presents estimates of the change in insurance coverage (among people admitted to the hospital) that occurs on the first day of the month after people turn 19. Directly below the estimates are the standard errors of the estimates and below the standard errors are the proportion of the population with this type of coverage immediately before people age out at 19. The estimates are made using a linear polynomial in age for estimated using admissions among people age 18 to age 20. The estimates of the change in insurance are adjusted for the effect of insurance status on the probability of getting treated.

Appendix 19: Assessing Sensitivity to Bandwidth Choice of the Estimate of the Change in Number of Men Admitted to the hospital at Age 19



Notes: The estimates above are the discrete change at age 19 from a local linear regression with a symmetric bandwidth. The heavy line is the point estimate and the lighter lines are the confidence intervals.

Appendix 20: Assessing Sensitivity to Bandwidth Choice of the Estimate of the Change in Number of Women Admitted to the hospital at Age 19



Notes: The estimates above are the discrete change at age 19 from a local linear regression with a symmetric bandwidth. The heavy line is the point estimate and the lighter lines are the confidence intervals. Pregnant women are not included in the analysis.

Appendix 21: Change at Age 19 in Admissions to the Hospital

	All Visits	Via Emergency Department	Not Via Emergency Department
	(1)	(2)	(3)
All	-0.0168	-0.0096	-0.0202
	[0.0057]	[0.0057]	[0.0082]
Arizona	-0.0250	-0.0140	-0.0293
	[0.0115]	[0.0168]	[0.0158]
California	-0.0201	-0.0019	-0.0263
	[0.0061]	[0.0102]	[0.0084]
Iowa	0.0366	-0.0179	0.0537
	[0.0317]	[0.0764]	[0.0362]
New York	-0.0123	-0.0161	-0.0092
	[0.0066]	[0.0072]	[0.0111]
Texas	-0.0079	-0.0096	-0.0071
	[0.0112]	[0.0166]	[0.0113]
Wisconsin	-0.0462	-0.0565	-0.0424
	[0.0202]	[0.0312]	[0.0309]

Notes: See notes from Table 8. The dependant variable is the log of admissions and the results are for overall admissions and split by route into the hospital

Appendix 22: Impact of Losing Insurance on Admissions to the Hospital

	All Visits	Via Emergency Department	Not Via Emergency Department
	(1)	(2)	(3)
All	-0.6135	-0.3509	-0.7376
	[0.2414]	[0.2208]	[0.3343]
Arizona	-0.8390	-0.4747	-0.9815
	[0.4905]	[0.5953]	[0.6397]
California	-0.7313	-0.0681	-0.9536
	[0.2719]	[0.3746]	[0.3685]
Iowa	-1.9372	0.9228	-2.8675
	[3.0015]	[4.1546]	[4.1342]
New York	-0.4788	-0.6263	-0.3597
	[0.2808]	[0.3167]	[0.4418]
Texas	-0.3108	-0.3793	-0.2822
	[0.4578]	[0.6721]	[0.4591]
Wisconsin	-0.5437	-0.6624	-0.5001
	[0.2679]	[0.4000]	[0.3862]

Notes: See notes from Table 9. The elasticities above are the impact of insurance on hospital admissions. They are computed by dividing the percent change in admissions by the percent change in the population that is uninsured.

Appendix 23: Change at Age 23 in Insurance Coverage and Emergency Department Visits

	Private	Uninsured	ln(Visits)	Instrumental Variables Estimate
	(1)	(2)	(3)	(4)
All	-0.0154	0.0170	-0.0142	-0.8267
	[0.0018]	[0.0028]	[0.0036]	[0.2517]
	0.3555	0.3111		
All (Except Pregnant)	-0.0170	0.0193	-0.0165	-0.8477
	[0.0020]	[0.0028]	[0.0037]	[0.2281]
	0.3651	0.3218		
Male	-0.0195	0.0230	-0.0212	-0.9107
	[0.0031]	[0.0041]	[0.0056]	[0.2930]
	0.3406	0.3995		
Female	-0.0117	0.0117	-0.0083	-0.7013
	[0.0018]	[0.0034]	[0.0055]	[0.5119]
	0.3640	0.2503		
Female Not Pregnant	-0.0140	0.0150	-0.0115	-0.7627
	[0.0020]	[0.0031]	[0.0053]	[0.3864]
	0.3833	0.2593		

Notes: The Emergency Department visits used to estimate the regressions are a near census of ED visits in Arizona (2005-2007), California (2005-2007), Iowa (2004-2007), New Jersey (2004-2007) and Wisconsin (2004-2007).The parameter estimates in the table above are the percentage point change in insurance coverage when people age out of their insurance coverage on the last day of the month in which they turn 23. The standard errors are in brackets directly below the parameter estimates. Below the SE we have included the estimated level of the dependant variable immediately before people age out. The parameter estimates are adjusted for the decline in admissions under the assumption that the decline in admission is due entirely to people losing their insurance coverage. The adjustment is made by estimating the insurance coverage regression and the ln(admissions) regressions via seemingly unrelated regression.

Appendix 24: Age Profile of Emergency Department Visits at Age 20