The Effect of Health Insurance Coverage on the Use of Medical Services

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WEB APPENDIX

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:

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

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.

I. 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.[1] 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:

[1] 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 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:

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)

A. 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 $\mathrm{E}[D_i(1) - D_i(0) \mid Y_i(0) = 1]$, 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:

$$
\begin{aligned}
&= \frac{\mathrm{P}(Y_i(1)=1 \cap i \text{ is LAT})}{\mathrm{P}(Y_i(0)=1)} - \frac{\mathrm{P}(Y_i(0)=1 \cap i \text{ is LAT}) + \mathrm{P}(Y_i(0)=1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)} \\
&= -\frac{\mathrm{P}(Y_i(0)=1 \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)} \\
&= -\mathrm{P}(i \text{ is LC} \mid Y_i(0)=1) \\
&= \mathrm{E}\left[D_i(1) - D_i(0) \mid Y_i(0)=1\right]
\end{aligned}
\tag{A4}
$$

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.

B. REDUCED FORM

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

$$\frac{y_1 - y_0}{y_0} \tag{A5}$$

We show that this estimator converges to

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

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

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

C. 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:

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

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.

II. 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 V; see footnote 29.) 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.

A. 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.

B. 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:

$$\begin{aligned}\operatorname{plim}\left(\frac{y_0-y_1}{y_0}\right)&=\operatorname{plim}\left(\frac{y_0/N-y_1/N}{y_0/N}\right)\\&=\frac{\mathrm{P}(Y_i(0)=1)-\mathrm{P}(Y_i(1)=1)}{\mathrm{P}(Y_i(0)=1)}\\&=\frac{\mathrm{P}(Y_i(0)=1\cap i \text{ is LAT})+\mathrm{P}(Y_i(0)=1\cap i \text{ is LNT})+\mathrm{P}(Y_i(0)=1\cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)}\\&\quad-\frac{\mathrm{P}(Y_i(1)=1\cap i \text{ is LAT})+\mathrm{P}(Y_i(1)=1\cap i \text{ is LNT})+\mathrm{P}(Y_i(1)=1\cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)}\end{aligned} \qquad \text{(A11)}$$

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:

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

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

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

C. 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.

D. Estimates From Emergency Department Data

The modified first-stage, equation (A10), is equal to –0.129 in the ED data.[2] The modified first stage thus generates a modified IV estimate of 0.254, as compared to the original IV estimate of 0.404. However, as noted above, 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:

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

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

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

[2] We count privately insured patients, Medicaid patients, and "other insurance" patients as insured. Taking the estimates from Tables 2 and 3, equation (A10) thus equals 2*(–0.0629 – 0.0166 –0.0015) + 0.033 = –0.129.

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:

$$\begin{aligned}(\text{A13}) \quad & \mathrm{E}\left[Y_i(D_i = 1) - Y_i(D_i = 0) \mid i \text{ is LC}, i \text{ is EAT}\right] \cdot \frac{-\mathrm{P}(i \text{ is EAT} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0) = 1)} \\ & + \mathrm{E}\left[Y_i(D_i = 1) - Y_i(D_i = 0) \mid i \text{ is LC}, i \text{ is EC}\right] \cdot \frac{-\mathrm{P}(i \text{ is EC} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0) = 1)} \\ & + \mathrm{E}\left[Y_i(D_i = 1) - Y_i(D_i = 0) \mid i \text{ is LC}, i \text{ is EDF}\right] \cdot \frac{-\mathrm{P}(i \text{ is EDF} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0) = 1)}\end{aligned}$$

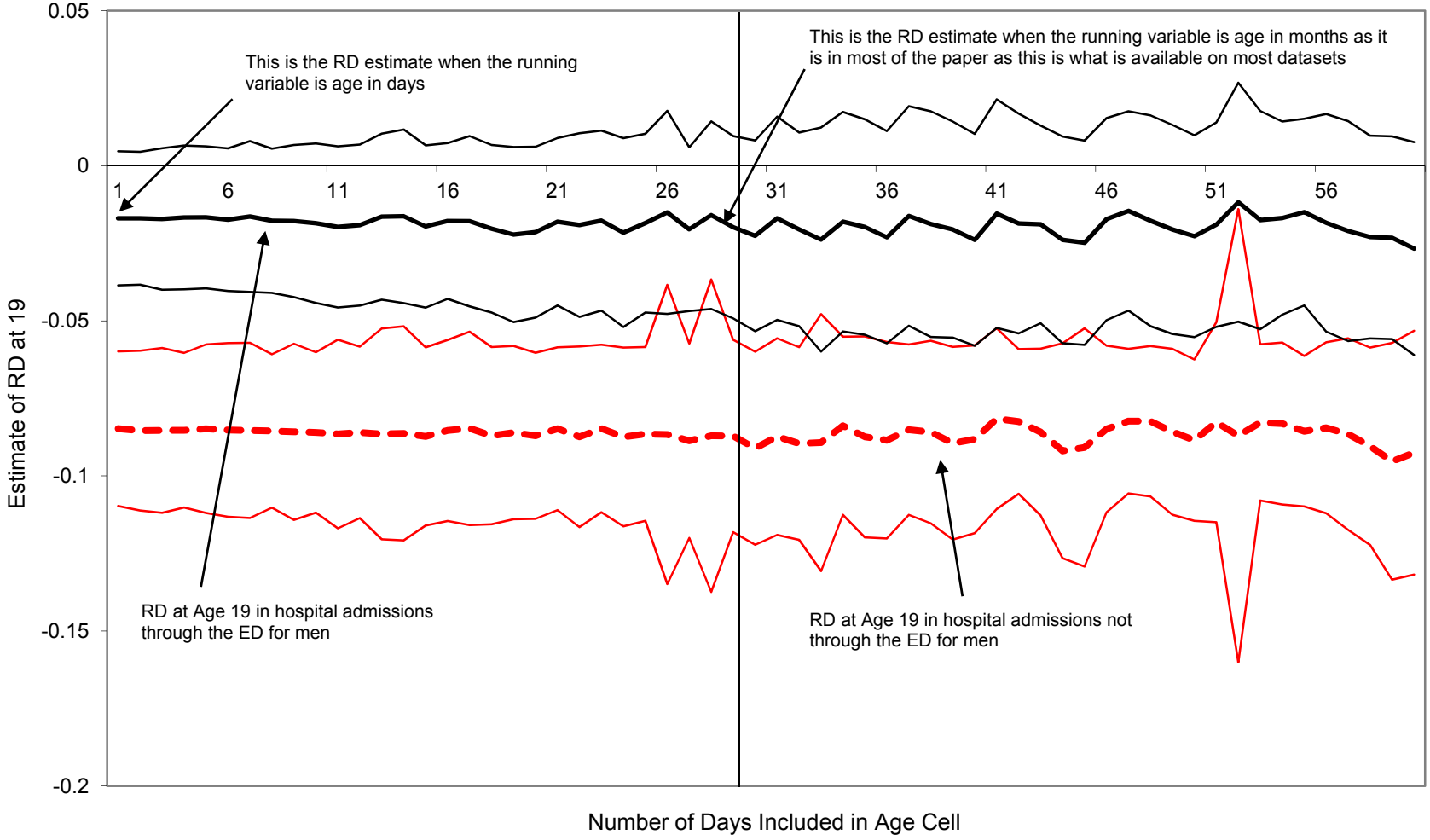
The reduced form therefore estimates a weighted average of three average causal effects: the average causal effect for LATE compliers who are extended always-takers, the average causal effect for LATE compliers who are "extended compliers" (individuals that visit the ED only when insured), and the average 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 2, 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 0.048 (given by 0.129 – 0.081 = 0.048). 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).

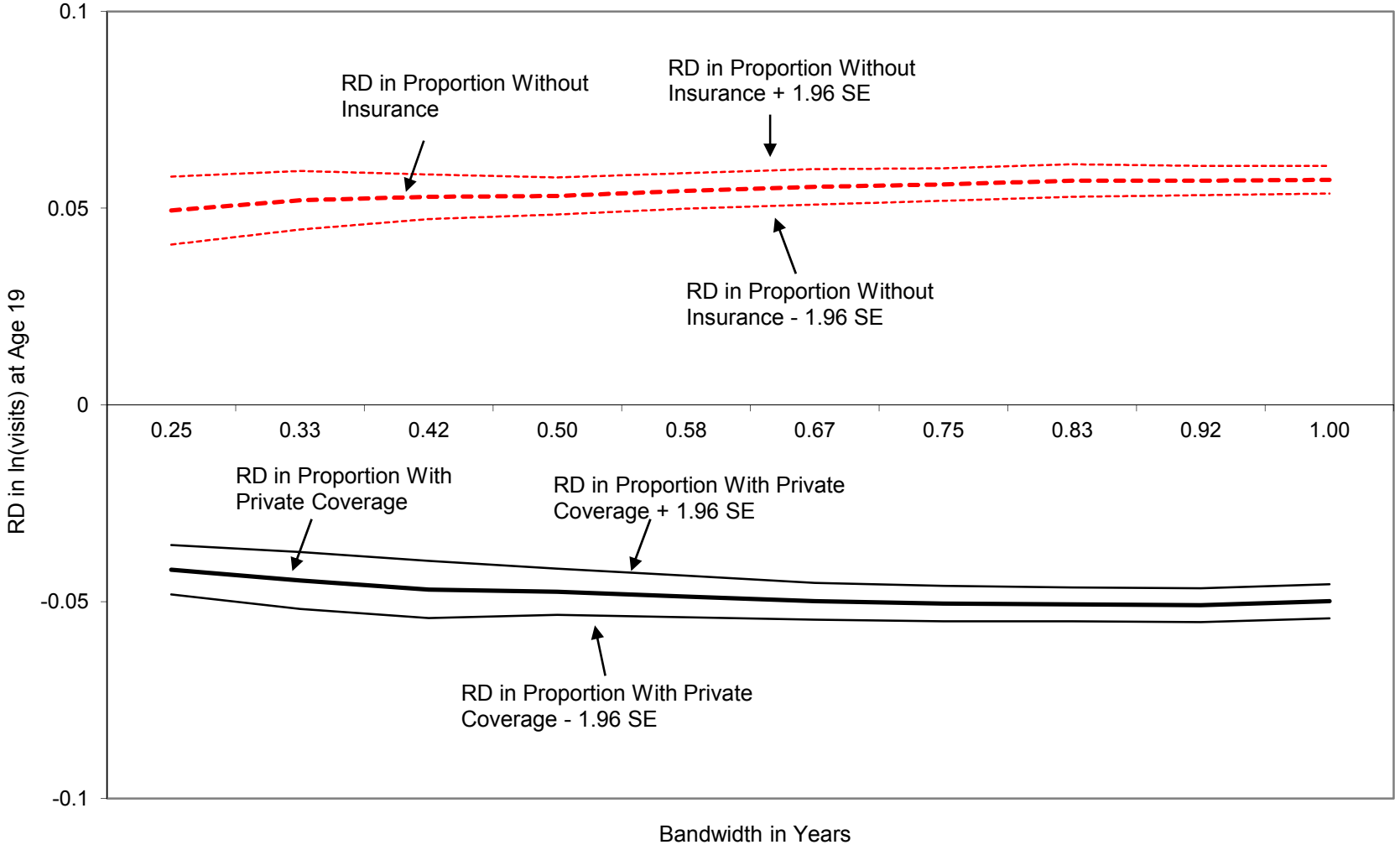
To establish an upper bound (in magnitude) on the sum of the three weights in equation (A13), we make the reasonable assumption that the number of LATE compliers that stop visiting the ED when becoming uninsured (extended compliers) is no greater than the number of LATE compliers that either continue 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 0.048, and thus $\frac{\mathrm{P}(i \text{ is EAT} \cap i \text{ is LC})}{\mathrm{P}(Y_i(0)=1)}$ is at least 0.033 (given by 0.081 – 0.048 = 0.033). We therefore adjust the modified first-stage estimator for double counting of extended always-takers by subtracting at least 0.033, and find that the modified first-stage estimator has an upper bound (in magnitude) of 0.096 (given by 0.129 – 0.033 = 0.096). A modified first-stage of –0.096 generates a modified IV estimate of 0.341. 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 34 percent.

Appendix Figure 1: Impact on RD Estimates of Coarsening the Age Variable from Age in Days to 60 Day Cells



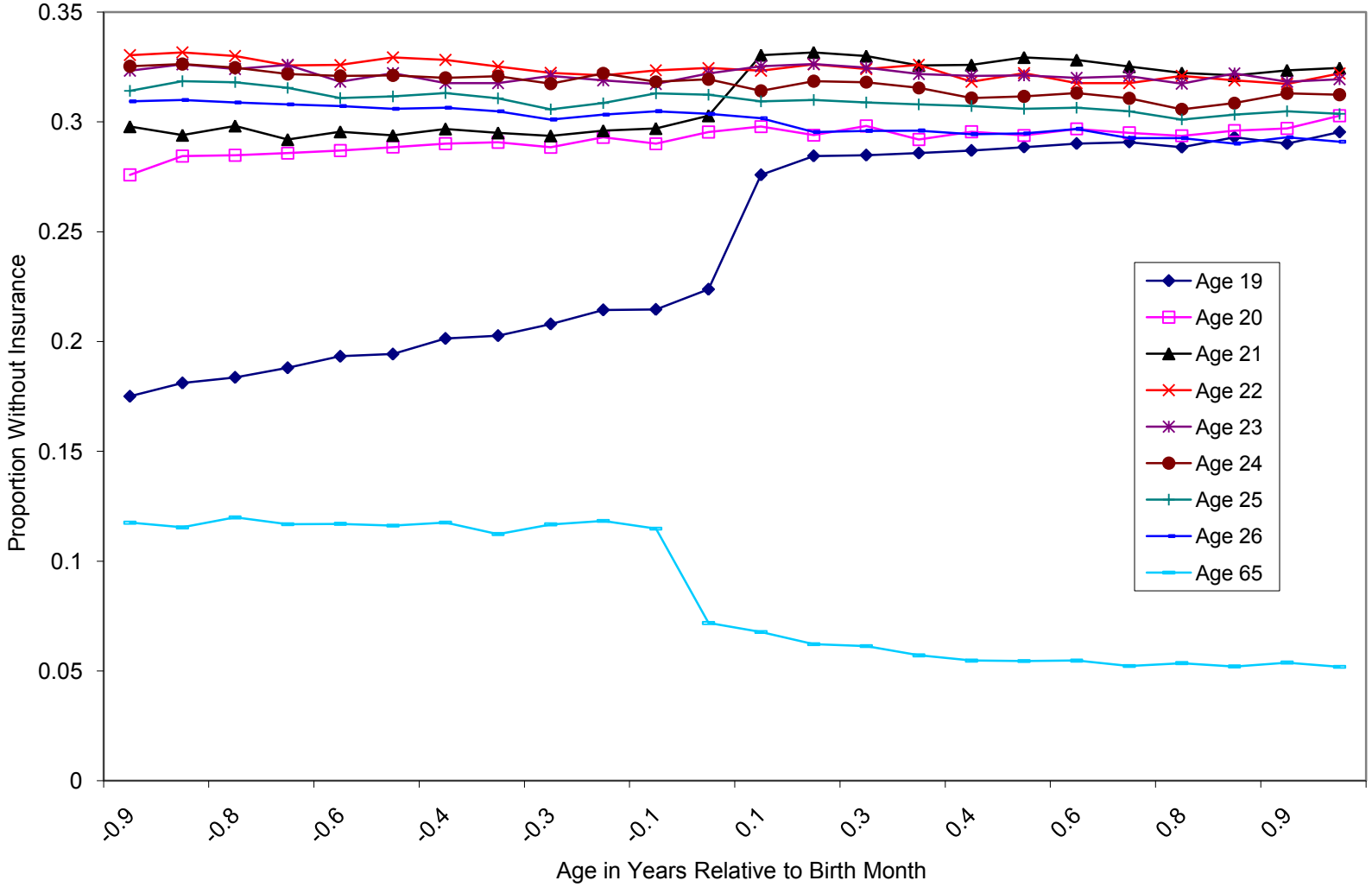
Notes: The regressions in the paper all have age cells of approximately 30 because age is typically only available in months. The heavy lines are the estimates of the RD and the lighter lines are the confidence intervals.

Appendix Figure 2: Assessing Sensitivity to Bandwidth Choice of Estimate of Change in Insurance Among People Treated in the Emergency Department

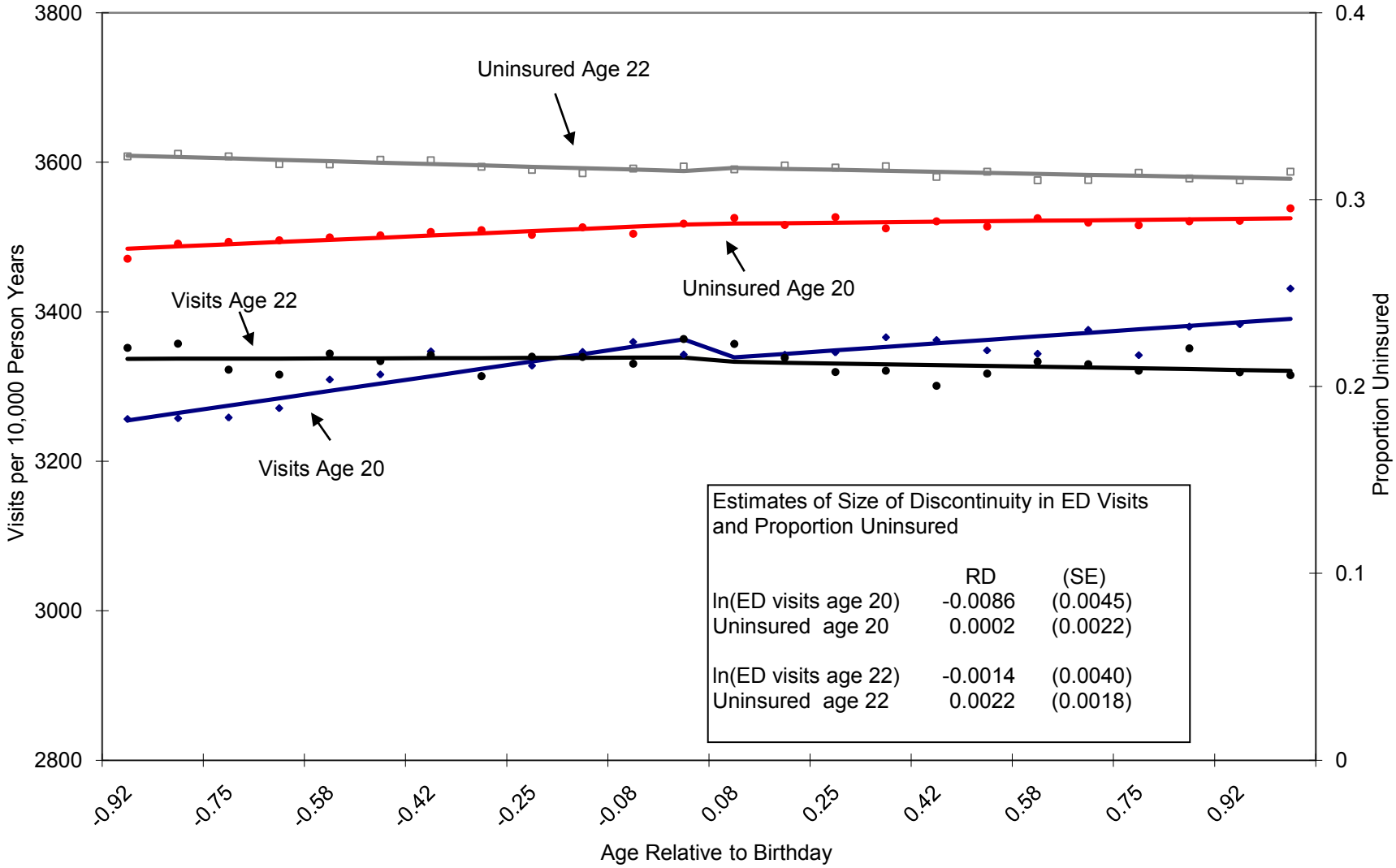


Notes: The estimates above are the discrete change at age 19 from a local linear regression with a symmetric bandwidth. The heavy line is the point estimate and the lighter lines are the confidence intervals.

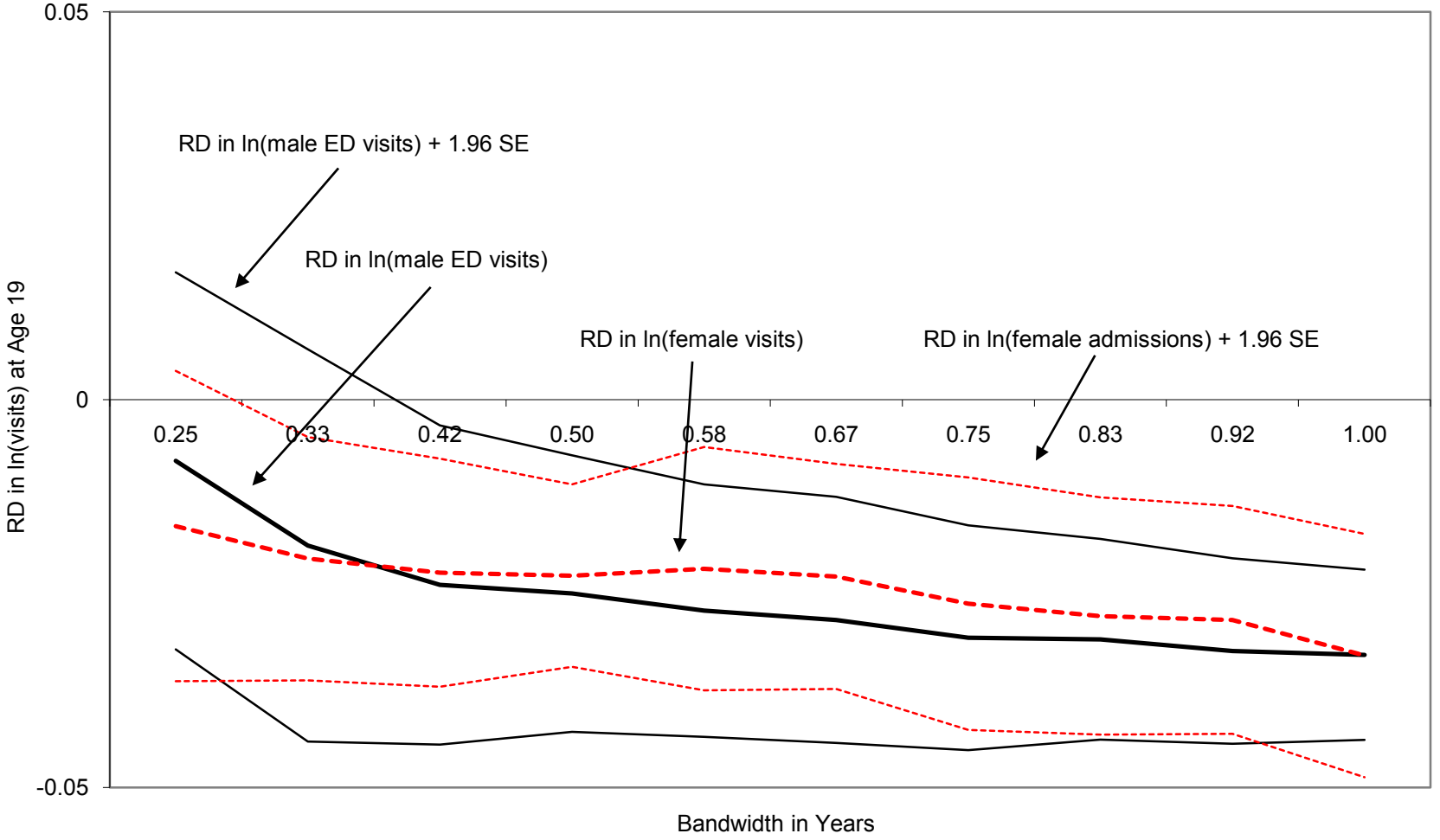
Appendix Figure 3: Age Profile of Proportion ED Visits Without Insurance Coverage Centered at Ages 19-26 and 65



Appendix Figure 4: Age Profile of Insurance and Emergency Department Visits at Age 20 and Age 22

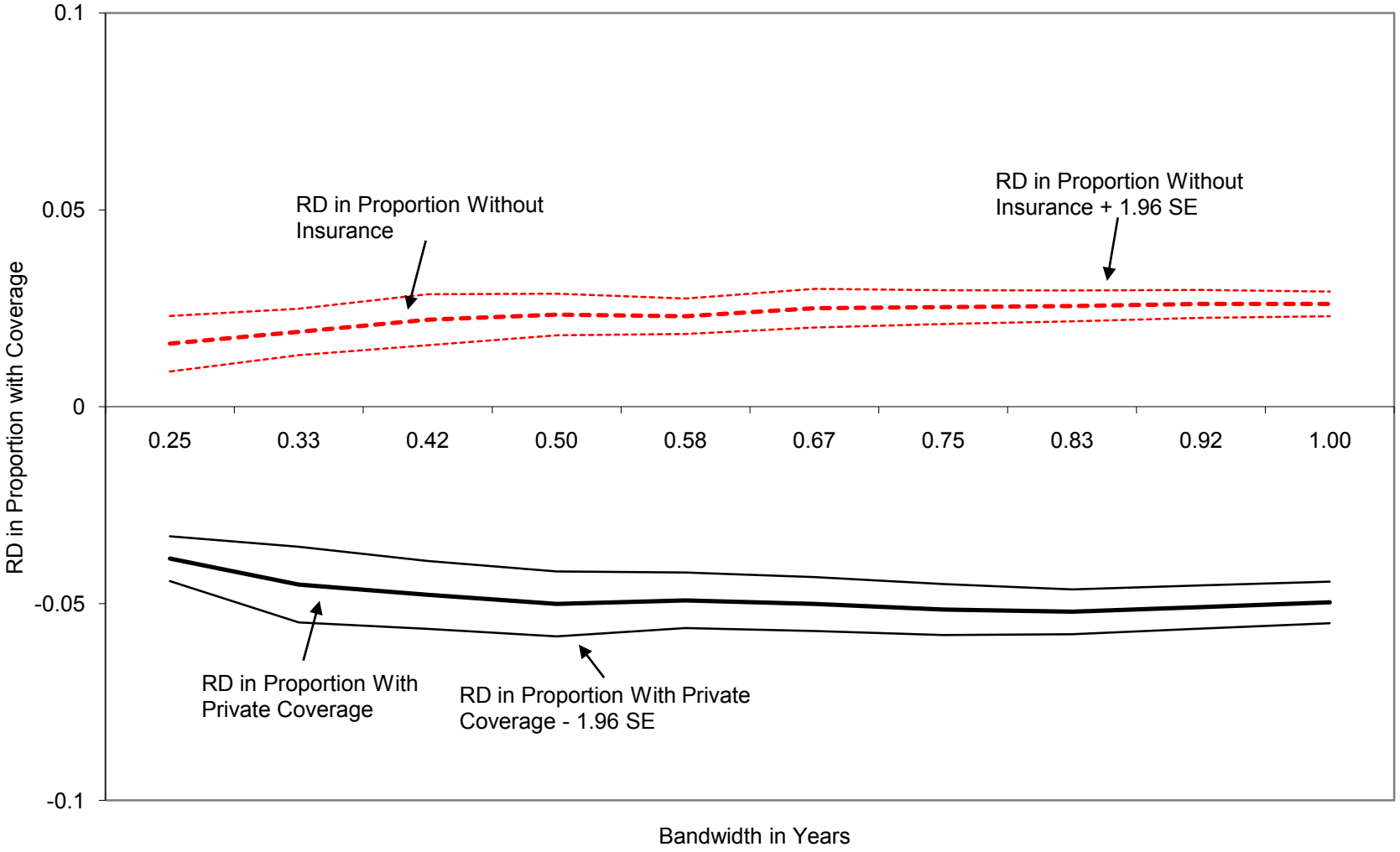


Appendix Figure 5: Assessing Sensitivity to Bandwidth Choice of Estimate of Change in Number of People Treated in the Emergency Department



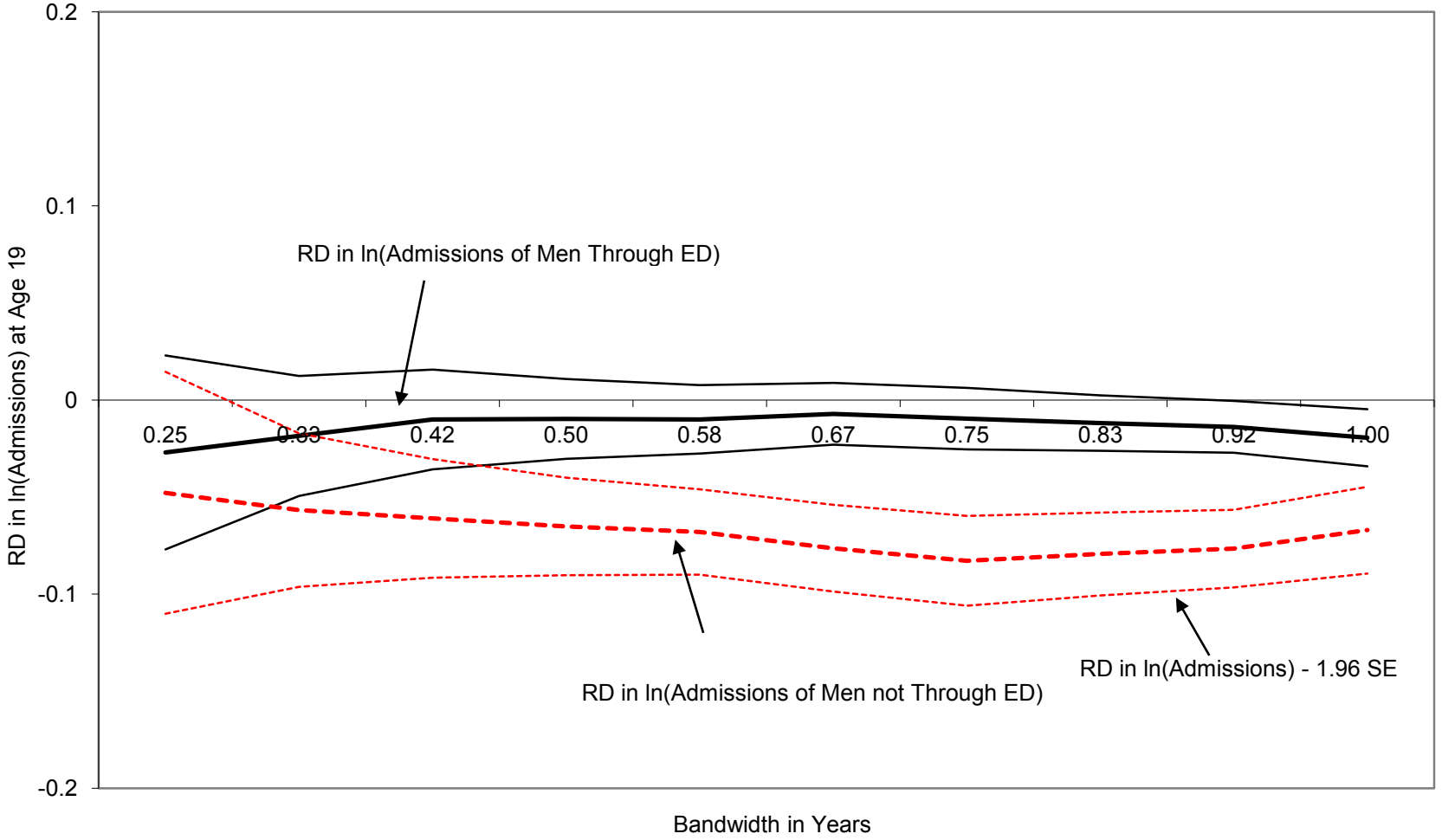
Notes: The estimates above are the discrete change at age 19 from a local linear regression with a symmetric bandwidth. The heavy line is the point estimate and the lighter lines are the confidence intervals.

Appendix Figure 6: Assessing Sensitivity to Bandwidth Choice of Estimate of Change in Insurance Among People Admitted to the Hospital



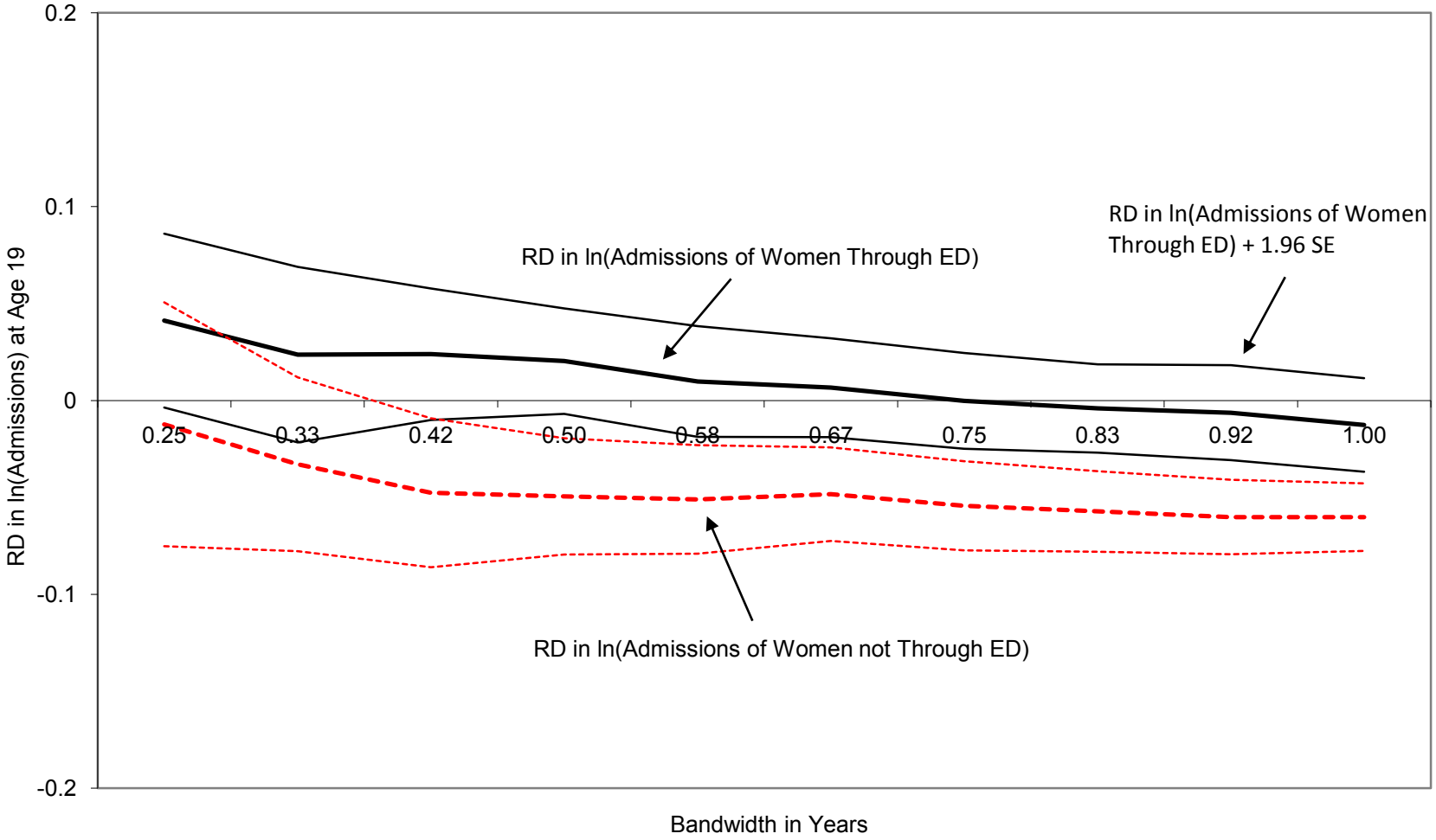
Notes: The estimates above are the discrete change at age 19 from a local linear regression with a symmetric bandwidth. The heavy line is the point estimate and the lighter lines are the confidence intervals. This figure only includes hospital stays that are not pregnancy related.

Appendix Figure 7: 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 Figure 8: 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 Table 1: Change at Age 19 in Insurance Coverage and Emergency Department Visits by State

	Private	Uninsured	Medicaid	Change in ED Visits	Impact of Losing Insurance on ED Visits
	(1)	(2)	(3)	(4)	(5)
All States	-0.0629	0.0810	-0.0166	-0.0333	-0.4041
	[0.0026]	[0.0046]	[0.0025]	[0.0060]	[0.0776]
	0.4471	0.2154	0.2644		
Arizona	-0.0459	0.0536	-0.0035	-0.0286	-0.5258
	[0.0052]	[0.0103]	[0.0059]	[0.0128]	[0.2600]
	0.3480	0.2063	0.3580		
California	-0.0659	0.0760	-0.0059	-0.0368	-0.4755
	[0.0036]	[0.0057]	[0.0029]	[0.0074]	[0.1038]
	0.4073	0.2141	0.2944		
Iowa	-0.0514	0.0740	-0.0209	-0.0444	-0.5862
	[0.0072]	[0.0105]	[0.0059]	[0.0136]	[0.2024]
	0.4935	0.1818	0.2654		
New Jersey	-0.0722	0.0851	-0.0144	-0.0164	-0.1908
	[0.0038]	[0.0044]	[0.0029]	[0.0080]	[0.0945]
	0.5637	0.2751	0.1180		
Wisconsin	-0.0613	0.1331	-0.0799	-0.0464	-0.3407
	[0.0068]	[0.0100]	[0.0060]	[0.0126]	[0.0982]
	0.4937	0.1490	0.2872		

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 (2004-2006). The parameter estimates in the columns 1-3 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 dependent variable immediately before people age out. The parameter estimates are adjusted for the decline in visits under the assumption that the decline in visits is due entirely to people losing their insurance coverage. The adjustment is made by estimating the insurance coverage regression and the log(visits) regressions via seemingly unrelated regression. The dependent variable in column 4 is the log of visits at each age in months. The estimates in column 5 are the ratio of the change in visits to the overall change in insurance coverage.

Appendix Table 2: Change at 19 in Insurance Coverage and Hospital Admissions for People that are Not Pregnant

	Private	Uninsured	Medicaid	Change in Hospital Stays	Impact of Losing Insurance on Hospital Stays
	(1)	(2)	(3)	(4)	(5)
All	-0.0664	0.0579	0.0088	-0.0379	-0.6411
	[0.0036]	[0.0048]	[0.0026]	[0.0050]	[0.1018]
	0.5003	0.1174	0.3050		
Arizona	-0.0665	0.0615	0.0081	-0.0477	-0.7583
	[0.0113]	[0.0179]	[0.0110]	[0.0213]	[0.4137]
	0.4646	0.0782	0.3380		
California	-0.0702	0.0558	0.0141	-0.0409	-0.7179
	[0.0034]	[0.0052]	[0.0037]	[0.0069]	[0.1412]
	0.4925	0.1095	0.3180		
Iowa	-0.0047	-0.0117	0.0269	0.0504	-4.4170
	[0.0438]	[0.0473]	[0.0254]	[0.0542]	[18.001]
	0.6423	0.0805	0.2367		
New York	-0.0645	0.0438	0.0231	-0.0260	-0.5857
	[0.0060]	[0.0075]	[0.0052]	[0.0079]	[0.2070]
	0.5115	0.1274	0.3163		
Texas	-0.0522	0.1090	-0.0562	-0.0638	-0.5670
	[0.0087]	[0.0142]	[0.0062]	[0.0176]	[0.1785]
	0.4888	0.1553	0.2034		
Wisconsin	-0.0953	0.1078	-0.0385	-0.0399	-0.3631
	[0.0183]	[0.0238]	[0.0135]	[0.0256]	[0.2512]
	0.6089	0.0756	0.2471		

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 (2004-2006). Combining the data from the six states gives a sample of 849,636 18 and 19 year olds. In columns 1-3 we present 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. In column 4 we present the change in ln(hospital stays) and in column 5 we present the impact of insurance coverage on hospital stays.

Appendix Table 3: Change at Age 23 in Insurance Coverage and Emergency Department Visits

	Private	Uninsured	Medicaid	ln(Visits)	Instrumental Variables Estimate
	(1)	(2)	(3)	(4)	(5)
All	-0.0154	0.0170	-0.0013	-0.0142	-0.8269
	[0.0018]	[0.0028]	[0.0013]	[0.0036]	[0.2517]
	0.3555	0.3111	0.2214		
All (Except Pregnant)	-0.0170	0.0195	-0.0023	-0.0167	-0.8496
	[0.0020]	[0.0028]	[0.0012]	[0.0037]	[0.2517]
	0.3651	0.3219	0.1952		
Male	-0.0195	0.0230	-0.0028	-0.0212	-0.9111
	[0.0031]	[0.0041]	[0.0013]	[0.0056]	[0.2517]
	0.3406	0.3995	0.1075		
Female	-0.0117	0.0117	-0.0004	-0.0082	-0.7010
	[0.0018]	[0.0034]	[0.0023]	[0.0055]	[0.2517]
	0.3640	0.2503	0.3048		
Female Not Pregnant	-0.0140	0.0150	-0.0016	-0.0115	-0.7625
	[0.0020]	[0.0031]	[0.0021]	[0.0053]	[0.2517]
	0.3833	0.2593	0.2710		

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 dependent variable immediately before people age out. The parameter estimates are adjusted for the decline in visits under the assumption that the decline in visits is due entirely to people losing their insurance coverage. The adjustment is made by estimating the insurance coverage regression and the ln(visits) regressions via seemingly unrelated regression.