Does Health Insurance Always Increase Health Care Demand? Evidence on Distributional Effects from Inpatient Hospital Stays

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Abstract

In quantifying the impact of insurance on health care demand, most quasi-experimental studies focus on mean spending and consumption, which, considering the highly-skewed shapes of spending and consumption, potentially hides important information about how insurance is related to health care demand. This paper, by contrast, examines the entire distribution of health care demand. To address insurance endogeneity, the paper focuses on inpatient hospital stays resulting from an emergency event. The main finding is that lacking insurance seems to hinder inpatient spending only for relatively light-spending stays. By contrast, for heavy-spending stays, which are presumably more serious medically, lacking insurance does not appear to hinder spending.

JEL Codes: I13, C21

Key Words: quantile regression, quantile counts, treatment effects

1 Introduction

Though health insurance often enters the discussion when the topic of health care spending arises, the influence of health insurance in relation to the distribution of health care spending is a topic that is rarely mentioned. US health care spending overall is highly concentrated among a small slice of the population. The top 5% of the spending distribution is responsible for almost 50% of total spending. The bottom 50%, by symmetric contrast, is responsible for less than 5% of total spending (Cohen, 2012). Relatively little attention has been paid to the concentrated nature of health spending among individuals and the role that health insurance may play in this context. We typically think of two primary ways that health insurance affects demand for services: 1) a moral hazard effect stemming from the lower point of service prices that health insurance affords and 2) an income effect for high dollar services that one would purchase even without health insurance given sufficient income. Differences in provider behavior across insurance status may also affect spending. The flip side of the net effect of these factors is of course the “access gap” with respect to those without insurance coverage. We might expect the relative influence of these effects and ultimately the “access gap” to vary considerably depending on the severity of patient episodes. This interaction between health insurance and the intensive utilization margin across treatment episodes is the focus of our study. Specifically, how does health insurance affect health care spending through the entire distribution of spending episodes?

The best evidence on the relationship between insurance and health care demand comes from the handful of policy experiments that have been conducted in the US. Most well-known is the RAND Health Insurance Experiment that took place in the 1970s. Participating families at 6 sites were randomly assigned to insurance plans with varying cost sharing features, including a plan with no co-insurance and a plan with 95% co-insurance. Manning et al. (1987) found that expenditures per capita were 45% higher in the plan with no co-insurance compared to the 95% co-insurance plan. The majority of the variation found as part of the RAND study was due to increases in the number of contacts with the medical system rather than the intensity of services provided during a contact.

More recent studies have taken advantage of natural or quasi-experiments to assess how health insurance affects utilization and expenditures. Card et al. (2008) assessed how aging into Medicare affected non-deferrable inpatient admissions. They find that Medicare increased the number of procedures performed in the hospital and led to a 3% increase in total charges. As part of a review of the evidence from the first year of the Oregon Health Insurance Experiment, a randomized experiment where potential Medicaid recipients were assigned to apply for the program by lottery, Baicker and Finkelstein (2011) and Finkelstein et al. (2012) document significant increases in outpatient care (+35%), prescription drug use (+15%), and hospital admissions (+30%). They estimate that this increased utilization resulted in a 25% increase in total annual health care expenditures as a result of the insurance expansion. In a paper whose methodology we follow, Doyle (2005) examines individuals admitted to hospitals following automobile accidents. He uncovers a gap of 20% in the treatment of the uninsured.[1]

Thus we have strong evidence on the impact of health insurance on additional episodes of care and some evidence on the increased intensity of episodes of care. In individual-level data, health insurance status likely is endogenous with respect to health care demand. To quantify the impact of insurance, researchers employ a variety of methods, and as already noted those based on quasi-experimental approaches

[1]See Currie and Gruber (1997), Bamezai et al. (2005), Anderson et al. (2012, 2013), Taubman et al. (2014) for other example of studies that use quasi-experimental methods.

receive the most attention. However, with few exceptions, those quasi-experimental studies focus on mean outcomes, potentially hiding important information about how insurance relates to health care demand, considering the highly-skewed shapes of demand measures.

This paper seeks to examine whether what is commonly referred to as the uninsured "access gap" persists and is consistent in magnitude across "low-intensity" and "high-intensity" hospital episodes, where we define the level of "intensity" according to the amount of health care services rendered. Our identification strategy rests on the assumption that inpatients stays precipitated by emergency room visits do not afford patients the opportunity to self-select insurance in anticipation of those emergency events. Using econometric jargon, by focusing on emergency-precipitated inpatient stays, insurance status should remain relatively exogenous with respect to health care demand for the duration of the inpatient stay. A similar identification strategy appears in an influential study by Doyle (2005), and we offer evidence in support of the approach in the context of the empirical application put forth in this paper as well.

Using data on inpatient stays resulting from emergency department visits, we consider three measures of “demand” per inpatient stay: total charges, total spending, and total number of nights spent in the hospital. We estimate how lack of health insurance affects those three measures using a quantile regression approach. We find that insurance status does not impact total medical charges for inpatient events, a finding that we interpret as offering support to our identification strategy, because it suggests that medical severity does not correlate with insurance status.

Lack of insurance does appear to reduce inpatient *spending*, but only for relatively light-spending inpatient stays. For relatively heavy-spending stays, insurance appears to have no relationship with total spending. We interpret this as encouraging news, in that to whatever extent lack of insurance hinders spending, that impact is concentrated among the lightest spending, and therefore presumably the least medically serious, inpatient stays. That is, insurance does not appear to significantly hinder access to medical services, at least not among emergency-precipitated inpatient stays. Finally, lack of insurance does not appear to result in fewer hospital nights, which we again interpret as encouraging news regarding access to inpatient-based medical care services. This work has the potential to inform policy makers on the distributional effects of health insurance on health care demand, an important topic given the substantial fraction of Americans predicted to gain coverage over the next few years as a result of the Affordable Care Act. Results from this effort also will have relevance in the discussion of optimal insurance design as it relates to reining in health care spending.

2 Data

The estimation sample comes from the 2000-2010 event files of the Medical Expenditure Panel Survey, collected and published by the Agency for Healthcare Research and Quality, a unit of the U.S. Department of Health and Human Services. Each data point corresponds to a hospital inpatient stay that began with a trip to an emergency room. Crucially for our identification strategy, discussed below, the primary reason for the ER visit was listed as "emergency" and not "diagnosis or treatment." (We do not include inpatient events related to pregnancies, nor do we consider inpatient stays with zero reported facility expenses.) We limit our analysis to inpatient stays for which the patient was younger than 65, as everyone 65 and older should have some form of hospital coverage through Medicare. Our final estimation sample includes 1,102 unique inpatient stays.

The three outcome measures of interest are (1) total charges for the inpatient stay; (2) total spending (from all sources) for the inpatient stay; and (3) nights spent in the hospital during the stay. Charges and spending both are expressed in 2010 dollars using the Medical CPI, and both include all facility and doctor services. The motivation for considering both charges and spending is that many insurance companies, especially those with significant bargaining power, might negotiate prices for medical services, such that charges conceivably could vary by insurance status, even for identical health care services.

The main "treatment" variable is a dichotomous indicator of whether the patient lacked any form of health insurance coverage, public or private, policyholder or not, during the survey round in which the inpatient stay occurred. The empirical exercise seeks to determine whether the three measures of demand differ depending upon the patient's insurance status.

Table 1 presents means and selected percentiles partitioned according to patient insurance status. The top set of numbers shows that mean charges appear similar across insurance states. On the other hand, sample means indicate that insured patients have higher-spending inpatient stays (approximately 27 percent higher spending) and longer stays (about 9 percent more hospital nights), compared to inpatient stays for which the patient lacks insured.

However, the remainder of the table illustrates that the largest proportional differences between insured and uninsured stays appears to be concentrated at the lowest percentiles. For example, at the 5th percentile of spending, insured patients spend almost 400 percent more than their uninsured counterparts, whereas as the 95th percentile of spending, insured patents spend only 2 percent more than their uninsured counterparts. Turning to total charges, uninsured patients appear to have higher charges both at the lowest and highest quantiles, although as discussed below, those differences do not appear to be statistically significant at conventional levels. Meanwhile, the percentiles for hospital nights appear similar across insurance states.

Table 2 reports sample means, partitioned by insurance status, for patient characteristics. Uninsured patients are more likely to report being black or Hispanic, and they are less likely to be employed. Otherwise, insured and uninsured patients do not appear to differ significant with respect to observed socioeconomic traits. The bottom two rows of the table report the proportion of patients who report "fair or poor" health, and the proportion who report usually wearing a seatbelt. Those two variables, which proxy for health status and risk aversion, are important for verifying our identification strategy, and are discussed in more detail in the following section.

3 Empirical Methods

The following subsection outlines our identification strategy, as well as possible threats to that strategy. We then proceed to discuss our econometric models, which are based on quantile regression methods.

3.1 Identification approach

The presence of insurance status in a health care demand regression raises concerns about endogeneity, because individuals presumably seek insurance, in part, due to expectations about their future health care needs. But borrowing inspiration from Doyle (2005), we posit that "emergencies," being largely unanticipated, do not afford patients the opportunity to select into insurance in anticipation of those emergencies. Consequently, we focus only on inpatient stays that commenced with an emergency, because once an emergency-precipitated inpatient visit has begun, insurance status should remain relatively exogenous with respect to health care demand *during that visit*. (Inpatient events for to pregnancy-related emergencies might be partially anticipated, which is why we remove events for pregnancy-related emergencies from our estimation sample.)

There are two main threats to our identification strategy. First, uninsured patients might have medical events that are more (or less) severe than those endured by insured subjects. However, as Table 1 suggests, and as results presented below verify, uninsured and insured patients appear to have similar total charges per inpatient stay. We interpret this as (informal) evidence that, in our estimation sample, medical severity does not depend upon insurance status. Of course, an alternative explanation is that insured patients might have more severe medical events, but insurance companies have managed to negotiate those charges downward, such that uninsured and insured stays appear to have similar charges. However, as reported toward the bottom of Table 2, insured patients do not appear to report worse health, as proxied by self-reported "fair or poor health." Consequently, we believe that uninsured and insured emergency-precipitated inpatient stays likely do not show different degrees of medical severity.

A second threat to our identification strategy is that insured patients might be more risk averse, which might correlate with smaller probabilities of winding up in the hospital in the first place. Although this conjecture is difficult to test, the bottom row of Table 2 suggests that insurance and uninsured patients do not differ in their degree of risk aversion, proxied by the frequency of seat belt usage. Consequently, we feel confident that insurance status does not correlate with risk aversion, at least not among the carefully defined population considered in this paper.

3.2 Quantile regression methods

This paper seeks to estimate the impact of being uninsured on inpatient spending and hospital nights across the distribution of those outcomes. For charges and spending, we first calculate its natural logarithm to reduce the inherent skewness in those measures. Using the logged versions, we then employ standard quantile regression methods (Koenker and Bassett, 1978) using the `qreg` command in Stata. For hospital nights, which are recorded as discrete nonnegative counts, we estimate a version of the quantile count regression model introduced by Machado and Silva (2005), using the `qcount` Stata program written by Miranda (2007) and detailed by Cameron and Trivedi (2009, pp. 220-224).

In all regression models, we include a standard set of explanatory variables: age, age squared, education, and dummies for female, black, and Hispanic. We also include dummies for married and employed, as both likely correlate with the probability of having health insurance coverage. We include a dummy for residing in a metropolitan statistical area, as proximity to a hospital facility likely correlates with incurring an inpatient stay. Finally, we include a dummy for whether the patient self-reports "fair or poor" health. (We do not include the "seatbelt" proxy for risk aversion listed in Table 2, due to the possibility that seatbelt usage could correlate with injury severity in the event of an automobile accident. Nonetheless, including that variable did not alter any of the findings presented below.)

4 Results

Tables 3, 4, and 5 present regression estimates for the three outcomes: inpatient charges, inpatient spending, and hospital nights. For comparison with previous studies, the tables report non-quantile estimates in the left-most panel. Our main focus are the coefficients of uninsurance. Figures 1, 2, and 3 provide a visual summary of the quantile estimates of those coefficients. The following subsection briefly mentions results for the control variables. We then turn to the impact of uninsurance.

4.1 Control variables

Focusing first on total charges in Table 3, OLS results indicate that females have 17 percent lower charges than their male counterparts. But quantile estimates suggest that the impact of being female is most pronounced for inpatient stays with higher charges. Focusing on the two extreme percentiles reported in Table 3, females have 31 percent lower charges at the 90th percentile of charges, but gender does not appear to be related to charges at the 10th percentile. Hispanic have higher charges throughout the distribution of inpatient charges, while blacks have higher charges only at the lowest percentiles. Married subjects have lower charges in the OLS model, but that negative coefficient loses significance in the quantile specifications. MSA residents have higher charges through the distribution. Finally, "fair or poor health" correlates with higher charges, but only at the lowest percentiles.

Table 4 presents similar models for inpatient spending. For the most part, estimates look similar to the charges estimates reported in Table 3, but with a few notable differences. First, despite blacks and Hispanics showing evidence of having higher charges in Table 3, those two minority states do not appear to be related to inpatient spending. Similarly, while "fair or poor health" leads to higher charges, it does not appear to significantly alter inpatient spending.

Finally, Table 5 presents estimates for length of stay, measured as the number of hospital nights. Females have shorter stays, with most of that impact concentrated at the upper end of the distribution of hospital nights. Blacks and Hispanics have longer stays, with most of that impact concentrated in the lower end of the distribution. Married subjects have shorter stays, with most of that impact appearing in the middle of the distribution. Finally, "fair or poor health" translates to longer stays across the entire distribution.

4.2 Impact of uninsurance

Table 3 reports that being uninsured does not appear to impact inpatient charges, either at the mean, or at other parts of the distribution of inpatient charges. This finding suggests that, among emergency-induced inpatient stays, medical severity does not appear to vary with respect to whether the patient has insurance. As noted above, we interpret this finding as offering support to our identification strategy.

Turning to spending results in Table 4, uninsured patients spend approximately 23 percent less than their insured counterparts. This estimate is similar to the 20 percent estimate reported by Doyle (2005). However, the remainder of the table indicates that the main impact of uninsurance appears to be concentrated at lower quantiles. For example, at the 10th percentile, uninsured patients spend 63 less than their insured counterparts, but once inpatient spending reaches the 50th percentile, the coefficient of uninsured is less than half the size of the corresponding OLS estimate, and statistically indistinguishable from zero. The coefficient of uninsured switches to positive, but remains statistically indistinguishable from zero, at the highest percentiles.

For the hospital nights outcome, negative binomial estimation reveals that uninsured patients have 9 percent shorter stays, although that estimate does not differ significantly from zero. This finding contrasts with Doyle (2005), who finds significantly shorter stays among uninsured patients. The remaining columns of the table show that the coefficient fails to achieve significance at the points along the distribution of hospital nights.

To ease interpretation of the quantile regression estimates, Figures 1, 2, and 3 graph the coefficients for quantiles .05, .10, ... , .90, .95, along with 90 percent confidence bands. Both figures also present non-quantile coefficient estimates, shown as horizontal lines.

Focusing first on Figure 1, the quantile estimates appear similar to the OLS coefficient across the entire distribution of inpatient charges, but, as demonstrated by the confidence bands in the Figure, at no point do the quantile estimates appear to differ from zero. Turning to Figure 2, for low-spending inpatient stays, uninsured patients have substantially lower spending than their insured counterparts. Moreover, at those lower quantiles, the difference between insured and uninsured spending is several orders or magnitude larger than suggested by the OLS estimate. However, once spending reaches the 20th percentile, the difference between insured and uninsured spending is indistinguishable from zero, and that difference remains insignificant for the remainder of the distribution of spending. Turning to hospital nights, the coefficient estimates remain indistinguishable from zero over the entire distribution of hospital nights, including at the lower quantiles for which uninsured appears to hinder spending.

5 Conclusion

This paper attempts to quantify the impact of health insurance on health care demand. In contrast to much of the extant research on this topic, which emphasizes mean spending and consumption, this paper examines the entire distribution of health care demand. To address insurance endogeneity, the paper focuses on inpatient hospital stays resulting from an emergency event.

Lacking insurance does not seem to correlate with the medical severity of an inpatient visit, as proxied by total charges. Lacking insurance does appear to hinder inpatient spending, but only for relatively light-spending stays. By contrast, for heavy-spending stays, which are presumably more serious medically, lacking insurance does not appear to hinder spending. In addition, although lacking insurance appears to reduce spending for light-spending stays, that reduced spending does not manifest itself through shorter stays. Rather, lengths of stay, as measured in hospital nights, are comparable across insurance states.

These results, particularly the differences in spending for the uninsured during low-cost episodes, have implications for policy as well as future research. Insurance status does not appear to be a decisive factor for high-spending hospital episodes that account for a large percentage of overall spending. In one sense this is positive news in that the uninsured do not appear to suffer spending disparities during more severe hospital episodes. Policies aimed at cost control clearly must focus on provider and institutional choices in this context. Insurance-based disparities for low-spending episodes, however, may impact the overall quality of patient care and may also affect the likelihood of a readmission within 30 days, both questions of critical importance for hospitals in the current era of health reform. At the individual level, it is important to consider the reality that patients and providers, even in emergency situations, are basing care decisions in part on insurance status. In the case that quality of care is unaffected by the observed spending disparities, providers and insurers would be interested in understanding the mechanism behind the choices made during these episodes. These questions outline important areas for future work.

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Table 1: Summary statistics for charges (in 2010 dollars), spending (in 2010 dollars), and hospital nights
(n = 1,102 inpatient stays)

	Mean	5th pct.	25th pct.	50th pct.	75th pct.	95th pct.
			Patient is insured (n = 990)			
Total charges	$38,871	$2,716	$9,943	$19,816	$38,412	$107,664
Total spending	$16,254	$1,736	$4,424	$7,327	$14,469	$49,395
Hospital nights	5.3	1	2	3	6	16
			Patient is uninsured (n = 112)			
Total charges	$36,948	$3,620	$10,472	$19,917	$36,590	$151,173
Total spending	$12,790	$470	$3,611	$6,970	$13,127	$48,527
Hospital nights	4.9	1	2	3	5	18

Table 2: Mean characteristics for patients
(n = 1,102 inpatient stays)

	Uninsured n = 112	Insured n = 990	Different at p<.05 level?
Age	40.0	42.1	no
Years of education	10.4	11.2	no
Female	0.53	0.52	no
Black	0.29	0.18	YES
Hispanic	0.31	0.15	YES
Married	0.40	0.44	no
Employed	0.32	0.45	YES
MSA residence	0.77	0.80	no
Fair or poor health	0.38	0.40	no
Usually wears seat belt	0.73	0.75	no

Table 3: Log inpatient charges

	OLS		.10 quantile		.50 quantile		.90 quantile	
	Coeff	St Err	Coeff	St Err	Coeff	St Err	Coeff	St Err
Uninsured	0.025	0.093	0.052	0.122	-0.001	0.128	0.065	0.212
Age	0.012	0.010	0.008	0.012	0.010	0.013	0.003	0.021
Age squared	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000
Years of education	0.006	0.011	0.004	0.013	0.013	0.013	-0.001	0.022
Female	-0.171	0.057	-0.030	0.073	-0.208	0.077	-0.309	0.127
Black	0.067	0.073	0.176	0.097	0.055	0.102	-0.107	0.169
Hispanic	0.365	0.090	0.406	0.106	0.316	0.111	0.466	0.184
Married	-0.125	0.064	-0.033	0.083	-0.091	0.097	-0.157	0.144
Employed	0.005	0.070	0.099	0.090	0.031	0.094	-0.074	0.156
MSA	0.437	0.070	0.323	0.091	0.386	0.096	0.549	0.158
Fair or poor health	0.113	0.068	0.183	0.086	0.132	0.090	0.010	0.149
Constant	9.075	0.139	7.943	0.164	9.061	0.172	10.501	0.285

Table 4: Log inpatient spending

	OLS		.10 quantile		.50 quantile		.90 quantile	
	Coeff	St Err	Coeff	St Err	Coeff	St Err	Coeff	St Err
Uninsured	-0.233	0.136	-0.634	0.189	-0.113	0.116	0.125	0.215
Age	0.003	0.011	0.002	0.019	0.011	0.011	0.003	0.021
Age squared	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Years of education	0.012	0.013	0.007	0.020	0.001	0.012	0.014	0.022
Female	-0.214	0.063	0.090	0.133	-0.197	0.069	-0.492	0.129
Black	0.024	0.080	0.116	0.151	-0.141	0.092	-0.016	0.172
Hispanic	-0.129	0.106	-0.196	0.164	-0.035	0.101	-0.006	0.187
Married	-0.002	0.071	0.131	0.129	-0.119	0.079	-0.071	0.147
Employed	0.047	0.077	0.050	0.139	0.061	0.085	0.165	0.159
MSA	0.270	0.072	0.235	0.141	0.206	0.086	0.539	0.161
Fair or poor health	0.091	0.073	0.187	0.133	0.046	0.081	0.027	0.152
Constant	8.477	0.143	7.174	0.254	8.473	0.156	9.548	0.290

Table 5: Hospital Nights

	NB		.10 quantile		.50 quantile		.90 quantile	
	Coeff	St Err	Coeff	St Err	Coeff	St Err	Coeff	St Err
Uninsured	-0.090	0.097	0.020	0.114	-0.056	0.076	-0.023	0.312
Age	0.003	0.011	0.005	0.010	0.021	0.009	0.010	0.019
Age squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Years of education	-0.020	0.011	-0.019	0.013	-0.013	0.009	-0.029	0.025
Female	-0.187	0.062	0.002	0.058	-0.070	0.053	-0.314	0.118
Black	0.152	0.083	0.239	0.073	0.140	0.078	0.115	0.251
Hispanic	0.121	0.094	0.327	0.093	0.168	0.075	0.136	0.155
Married	-0.183	0.068	-0.096	0.063	-0.236	0.061	-0.137	0.183
Employed	-0.061	0.070	-0.063	0.066	-0.130	0.059	-0.079	0.160
MSA	0.197	0.079	0.113	0.082	0.083	0.064	0.244	0.181
Fair or poor health	0.278	0.069	0.252	0.065	0.196	0.056	0.356	0.151
Constant	1.425	0.168	0.198	0.122	0.794	0.126	2.077	0.443

Figure 1: Coefficients of uninsured in log charges regressions
(Dotted lines give 90 percent confidence bands for quantile estimates)

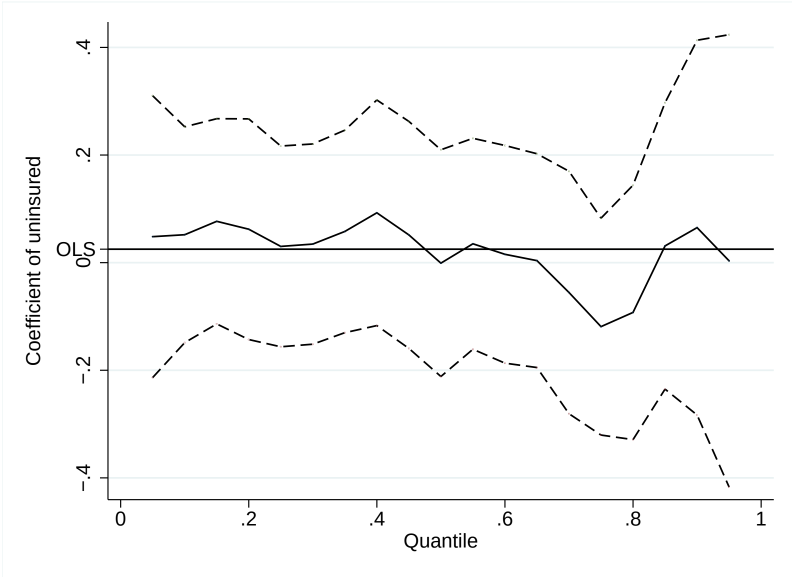

Figure 2: Coefficients of uninsured in log spending regressions
(Dotted lines give 90 percent confidence bands for quantile estimates)

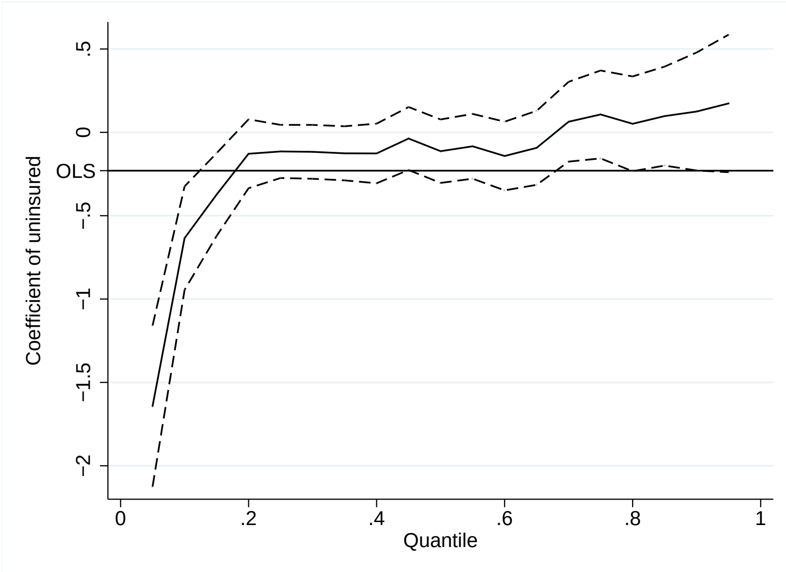

Figure 3: Coefficients of uninsured in hospital nights count regressions
(Dotted lines give 90 percent confidence bands for quantile estimates)