Volume Title: Doctors and Their Workshops: Economic Models of Physician Behavior

Volume Author/Editor: Mark Pauly

Volume Publisher: University of Chicago Press

Volume ISBN: 0-226-65044-8

Volume URL: http://www.nber.org/books/paul80-1

Publication Date: 1980

Chapter Title: Hospital Beds, Hospital-oriented Physicians, and Hospital Use

Chapter Author: Mark Pauly

Chapter URL: http://www.nber.org/chapters/c11526

Chapter pages in book: (p. 91 - 110)

6 Hospital Beds, Hospital-oriented Physicians, and Hospital Use

In the previous chapter, I identified some effects on use of physicians' own services which may be caused by physician availability. Some kinds of physicians' services, such as surgical treatment, almost surely imply additional use of hospital facilities as well. In this chapter, I wish to investigate more deeply the determinants of hospital use, and of those physicians' services provided in connection with hospitalization, especially with regard to the relationship between the availability of hospital and physician inputs and hospital use.

The Relationship between Hospital Inputs and Use

There seems to be little a priori reason to expect that the availability of hospital inputs should lead to physician creation of demand for hospital care, and physicians seem to be the only group with the ability to create demand for hospital admissions. That is, there is no obvious reason why the mere availability of hospital inputs should lead a physician to try to affect patients' demand for medical care. If hospital inputs can be obtained at some vector of prices, the level of those inputs that would be chosen by a real-income-maximizing group of physicians will be based on the output to be produced and the relative prices (net of insurance) of hospital and other inputs. But this choice of inputs is simply the derived demand for inputs—it is determined by the demand for final output. It does not in any way determine that demand. The only connection between inputs and final output is through the effect of input prices on the quantities of inputs chosen, and on the consequent effect of those input costs on the price of final output. In this sense, the level of hospital inputs is wholly endogenous, and the availability or quantity of such inputs would not affect use in a casual sense. If hospital inputs are wholly endogenous, the quantities of those inputs should not affect the provision of information or any other way of shifting demand.

There are, however, reasons to suppose that the quantity of hospital inputs may not always be set at the level which physicians would demand. The most likely outcome is that the level of inputs will be low relative to what physicians would demand, so that excess demand will be observed. There are three possible causes of such an outcome. First, even if the hospital is run in the interests of physicians, there may be limitations on the hospital's ability to raise equity capital, which may in turn restrict its ability to provide physical or working capital. The number of donations to the hospital may have a direct influence on its capital stock, and may also affect the terms at which it can borrow. Second, the hospital's administration or trustees may not want to provide the inputs physicians and patients desire. It is an open empirical question whether the hospital's administration has the power to implement its desires, or, if it does, how one might characterize its preference function. But it is surely possible that it may choose not to provide inputs which physicians want, so that there will be excess demand. (Alternatively, the hospital may desire to provide facilities that patients and physicians do not want.) Finally, since demand for hospital services is stochastic, there will almost surely be temporary periods of excess demand (or excess supply) at the profit-maximizing level of inputs or even at other higher input levels. The self-limiting nature of many illnesses, or the possibility of substitution of ambulatory care for inpatient care, may turn such temporary shortages into permanent reductions in demand.

It is also possible that donations may be so large that the hospital has more capital than physicians would have desired if the opportunity cost of the capital had had to be covered by hospital charges. Such excess capital is, in the physicians' view, equivalent to donation of the implicit interest. It would, nevertheless, be expected to be put to use. In this sense, if the marginal unit of capital is raised from donations, actual capital stock may be treated as exogenous.

In what follows I will consider each of these three possible reasons for an availability effect for hospital care. The goal will be to see what they imply about the possible existence and causes of that effect. For purposes of present discussion, the supply of physicians will be taken to be exogenous.

Permanent Excess Demand

Suppose that hospitals are restricted in their ability to add beds, even though physicians acting as perfect agents would demand those beds for patients with some level of insurance coverage. Since the hospital must price approximately at average costs, there is no direct way in which the hospital price can be raised to ration demand. Feldstein has suggested that, in such circumstances, the physician will be under pressure to share capacity with others.[1] While this may be so, some form of nonprice rationing would obviously have to be used even in the absence of explicit pressure. Conversely, were there no excess demand, bed availability should not have a direct effect on the physician's desire to use beds or on the advice he gives to patients. The physician who is a perfect agent will only want to ration care if there is excess demand. He may try to keep "his" beds free in order to take care of an unexpected case; if the number of beds increases, he can admit more patients and still maintain the same safety margin. It is this excess demand, not the pressure on physicians, which is likely to be the ultimate cause of an availability effect. Any pressure on physicians, implicit or explicit, is only a manifestation of excess demand already present.

In the longer run, Feldstein describes a process of hospital price adjustment to excess demand that comes about through increases in the costliness, input intensity, and the quality of hospital care. What he ignores, and what may be critical, is the role played by physicians and *their* prices for services they provide in connection with inpatient care. Feldstein does provide a discussion of physician ambulatory services. As he suggests, these services may well be substitutes for hospitalization, and the conventional opinion is that there is a "shortage" of such primary care services. In such a case, the quantity supplied of such services, i.e., the position of the supply constraint, would indeed be more relevant than the price in determining actual use. The situation is more complicated if some observations display excess demand and some do not. Then prices may be relevant as well, although the precise econometric specification of the relationship is unclear.

But the point that Feldstein omits is that many physician services are complementary to hospital use. In the case in which the demand-for-admissions function can be written $Q_H = Q(P_M + P_H)$, where P_M is the physician's user (net of insurance) price (e.g., the uncovered portion of the surgeon's fee) and P_H is the hospital's user price, there is obviously a very strong form of complementarity. It implies not only that $\partial Q_H/\partial P_M < 0$, but that $\partial Q_H/\partial P_M = \partial Q_H/\partial P_H$.

Such strong complementarity would have important implications for the existence of permanent and continuous excess demand for hospital services. If there is no excess demand for hospital-oriented physician services such as surgery (which almost surely is the case), there can be no excess demand for hospital services either. Suppose demand and supply of hospital admissions are equated (given insurance coverage) at some set of prices $\bar{P}_M$, $\bar{P}_H$. Now let P_H be depressed below $\bar{P}_H$, to P_H', but with no corresponding increase in supply. Excess demand for hospital services will occur. Hospitals may choose not to raise their prices.

But this excess demand can also be eliminated by a rise in the price of physicians' services to P_M' so that $P_M' + P_H' = \bar{P}_M + \bar{P}_H$. If physicians' prices are sufficiently flexible upward, even a "shortage" of hospital beds need not lead to permanent excess demand.

Feldstein's explanation is that excess demand is gradually reduced as hospitals raise their prices and costs by shifting to higher "quality" care. The alternative explanation here is that at least part of the price rise occurs as increased physicians' fees. With the definition of what constitutes a physician's service and what constitutes a unit of hospital output fixed, there appears to be no alternative to this form of strict complementarity. As long as hospitalization requires fixed proportions of both hospital and physicians' services, such an explanation will be the appropriate one. Feldstein's explanation of how equilibrium is achieved in the market for hospital care may be seriously misleading.

Is there any sense in which a rise in the user price of hospital service would not have an effect on the demand for hospital services equal to that of a similar rise in the price of physicians' services? To the extent that the ratio of hospital to physician inputs can be varied, such a difference is surely possible. A decline in the user price of a day of stay, e.g., the room rate, will increase the demand for hospital admissions, but it will also lead to an increase in desired length of stay. Physicians' charges typically do not vary with length of stay or with other amenities. However, even here, since the same input (beds) is used to produce both admissions and days of stay, there cannot be an excess demand for beds. The supply of beds can be rationed by altering the number of admissions as well as by altering length of stay. Indeed, if physicians collectively can exert some control, one would expect them to favor a stay-intensive "bed rationing" policy, one which concentrates on shortening stays, rather than on an admissions-intensive policy, precisely because physician income depends more on admissions than length of stay.

The above discussion suggests that when beds are in short supply, physician prices will be higher, and it suggests that hospital prices alone may give an adequate explanation of hospital demand only if user prices P_M and P_H are highly correlated. Such correlation is probably present in general; whatever the case with gross prices, hospital insurance coverage and insurance for physicians' services in hospital are highly correlated (as one would expect, since they are really the "same" insurance). What is critical, of course, is whether physician prices are sufficiently flexible upwards so that they will clear the market. At this point, we do not know whether they are or not.

Another less likely possibility is that there may be excess supplies of beds. This would generally result from incorrect planning, from demand shifts, or from overly generous public subsidies or private donations.

From the viewpoint of the hospital's administration or trustees, using those empty beds would probably be desirable. But there are no direct incentives to physicians to have them filled, no direct physician gain from admitting an additional patient whom the physician would not have wished to admit in the absence of empty beds. The hospital's financial condition can, however, have some *indirect* effects on physician decisions. If filling an empty bed reduces a deficit that threatens hospital survival, physicians collectively may agree to shift or tailor patient demand to fill empty facilities.

If the hospital is not in such difficulties, filling empty beds may still mean additional hospital profits (or smaller losses). Whether or not filling empty beds increases hospital profits depends on how the hospital is paid. If insurance pays wholly on the basis of costs, additional filled beds may please the administrator who values output, but they do not add to profits as long as incremental insurance reimbursement exactly equals incremental cost. If reimbursement exceeds marginal costs, and if filling of empty beds does not seriously affect the hospital's ability to handle peaks in demands, then physicians might be willing to create some additional demand if *they* can benefit in some way from the hospital's increased flow of profits.

One avenue of benefit would be the use of profits from filled beds to subsidize other outputs the hospital produces. Since the amount the physician can collect for the physician-hospital joint product increases as the hospital price is reduced, such a strategy would be a way of transferring the hospital's profits to physicians. Since the utility loss to the physician from increasing demand above what he would have chosen in the absence of excess beds is initially very small, and since the gain to him from hospital profits is positive, some demand creation would make him better off. A second strategy is for the hospital to use the additional profits for capital improvements which enhance physician income or utility. This strategy would be more likely to be chosen if the hospital could not transfer its profits directly to physicians. If it could transfer profits, the hospital which happens to have earned profits would make investments it would not have made in the absence of funds from profits only if there were restrictions on its ability to borrow. Note that, in all cases, the incentive to increase hospital demand must be imposed *collectively* on physicians. Otherwise, each individual physician would prefer to ride free; he would prefer to maintain his own level of accuracy while gaining from the hospital profits generated by other physicians' demand creation efforts.

Thus it is theoretically possible for an excess supply of beds to induce physicians to engage in more information manipulation, although the connection between an individual physician's reduction in accuracy and his income is not nearly so direct as for physicians' services themselves. Whether or not bed-availability effects actually do differ across education-information groups provides a test of the coincidence between theoretical possibility and reality.

Physicians and Hospital Administrators

If permanent excess demand does not necessarily arise from supply side restrictions, can it arise because hospital administrators refuse to provide beds that physicians and patients both demand and are willing to pay for through insurance? Such an event surely seems implausible. It is more likely that hospital administrators will desire *more* output than do physicians. Indeed, the supply of beds might be expected to be restricted by a physician cartel, but such restrictions would probably be opposed by individual hospital administrators.

Even empty beds may satisfy the administrator's desire for a large plant to manage. Of course, empty beds may also embarrass him or cause him financial difficulties.

Stochastic Demand

A more likely explanation for excess demand for hospital beds than any of those discussed so far is provided by the stochastic nature of demand. There can be *temporary* excess demand. The reason is simple: it will not ordinarily be desirable to build a hospital of such a size that there will never be excess demand, and it is impossible to vary prices to eliminate temporary shortages. Beyond some point, beds cannot be substituted for other inputs, or vice versa, to permit the hospital to deal with all levels of demand. So there will sometimes be excess demand; the level of total hospital demand will be inversely related to the probability of shortage, and directly related to bed supply. If the hospital is sometimes full, ambulatory care may be substituted, or the patient's condition may cure itself while he waits for a bed. Whatever the mechanism by which the choice is made, not all communities will end up with the same probability of shortage. Those communities in which the probability is smaller will, of course, have more use of hospitals. The possibility of temporary excess demand, therefore, provides a plausible explanation for an effect of hospital beds on hospital use.

When a hospital does happen to be full, there will be pressures on physicians to ration beds. One would expect that this rationing would have to be done on some collective basis, even if only implicitly. Physicians may even manipulate information to reduce the level of demand to hospital capacity. The critical point, however, is that physician behavior is solely a response to excess demand, and does not require a separate theory of demand creation. There may still be some differences between educational groups in the extent to which their demands can be affected by whatever form of nonprice rationing physicians choose, although there is no a priori reason to expect differences.

Physicians and Hospital Use

What might be the effect of physician availability on hospital use? For those physicians who primarily provide substitutes for inpatient care, such as general practitioners, use of hospital services might be expected to decrease with an increase in the absolute or relative number of such physicians (prices held constant), if there is an availability effect on the demand for ambulatory services. Where there is no such effect, only the relative prices of hospital substitutes would be relevant. With regard to hospital-oriented physicians who provide complementary inputs, such as surgical specialists, anything that increases the use of these physicians' inputs will also increase the use of the associated hospital inputs. It is generally agreed that there is an excess supply of many of these complementary physician inputs, especially general surgeons. An observed availability effect is therefore unlikely to arise from even temporary excess demand. If a physician availability effect occurs, it almost surely must come from information manipulation. For some other specialties, such as internal medicine, the prediction is ambiguous, since we do not know whether they are primarily producers of substitutes for or complements to hospital care.

If there is true demand creation, one should therefore look for an availability effect running from surgeon stock to use of surgeons' services in hospital. That such an effect exists has been suggested in the empirical literature, most strongly by Bunker, who found high rates of surgery matched by high rates of surgeons per capita in a comparison of the United States to England and Wales.[2] Lewis found that for some (but not all) surgical procedures there was a significant relationship between surgeon availability and surgery.[3] Wennberg and Gittelsohn also found this relationship, especially at the extremes of their small number of observations, but it seemed to break down at the level of individual surgical procedures.[4] This is perhaps not unexpected; there is no reason to suppose that demand creation, if it occurs, necessarily takes the same form everywhere.

Empirical Tests

The basic form and set of exogenous variables for the hospital demand equations that are presented in the next section are the same as for the physician visit equations in chapter 5. Independent variables are defined in the same way. Since federal hospital beds are not included in the measure of BEDS*, persons with episodes in federal hospitals were dropped from this sample, reducing the sample size slightly from that used in chapter 5.

Because any effect of beds on use will probably not come from information manipulation, there is no a priori expectation that there will be a difference between education-information groups in the coefficients measuring the effects of bed availability on either length of stay or admissions. If education somehow proxied time cost, and given suitable differences in the form of the demand function, some differences might emerge, but it would be difficult to predict them a priori. Indeed, the effect of stochastic excess demand may be too small to detect, especially if the occupancy rate is low enough that the hospital is rarely full.

Length of stay should depend primarily upon hospital and patient variables, but not directly on physician availability or price. One caveat is, however, suggested by the results in chapter 3. If a larger number of physicians per capita means more physician time spent at the hospital, this additional input may reduce length of stay. Since we have no accurate measure of the price of such an input, but only an overall index of physician medical or surgical fees, it is possible that in those areas where there are relatively many physicians and in which patients demand larger amounts of physician inputs per day of stay, stays may be shorter. Such an inverse relationship between physicians per capita and stay may be telling us more about production technology than demand.

Physicians would be most likely to have a demand-creation effect in the case of those hospital admissions in which surgery is performed. The surgically treated episode measures both the output which is of concern to the surgeon—the surgical procedure he performs—and the use by the patient of complementary hospital inputs. The relevant measure of availability here would be surgical specialists per capita. The fraction of physicians who are G.P.'s is also included in order to measure, in a crude way, the possibilities for substitution of nonsurgical for surgical forms of treatment. The physician price variable for surgically treated episodes (MDFEE) is a weighted average (over general practitioners and specialists) of the 1973 Medicare prevailing charge for hernia repair. For total hospital episodes, the followup office visit fee is used as a general index of physician fee levels. Finally, the number of hospital-based physicians per capita is included to take account of possible substitutes for surgical specialists. Ideally, we would like to have known the fraction of hospital-based physicians who are surgical specialists, but this fraction should be highly correlated with the total.

Results

Table 6.1 indicates the results for tobit and OLS regressions using hospital admissions as the dependent variable. While some persons had

Table 6.1 **Annual Hospital Episodes Regressions, All Episodes (Tobit and OLS Procedures)**

	Regression Coefficients (t statistics in parentheses)											
	22 Largest SMSAs				Other SMSAs				Nonmetropolitan Areas			
	Low Head Education		High Head Education		Low Head Education		Education High Head		Low Head Education		High Head Education	
Independent Variable or Statistic	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS
RAD	.108	.025	.157	.037	.115	.024	.138	.039	.135	.039	.095	.021
	(6.47)	(10.2)	(5.76)	(10.4)	(5.91)	(8.21)	(5.84)	(9.00)	(7.96)	(12.7)	(3.54)	(5.42)
CONDS	.431	.059	.246	.013	.427	.054	.480	.070	.436	.328	.064	.039
	(7.93)	(8.87)	(2.95)	(1.54)	(7.10)	(7.17)	(7.38)	(7.80)	(8.68)	(8.33)	(5.12)	(4.93)
AGE LT 15	−.308	−.041	−.603	−.073	−.591	−.060	.040	−.015	−.441	−.053	−.202	−.050
	(−1.46)	(−2.02)	(−2.13)	(−3.02)	(−2.52)	(−2.62)	(.19)	(−0.64)	(−2.11)	(−2.18)	(−0.88)	(−2.11)
AGE 45–64	.241	.004	.293	.022	.095	.006	.555	.043	.523	.049	.809	.070
	(1.29)	(0.22)	(1.05)	(0.95)	(0.45)	(0.30)	(2.62)	(2.31)	(2.87)	(2.23)	(3.67)	(3.10)
AGE 65+	.425	.030	.733	.099	.198	.015	.954	.150	.456	.058	.656	.641
	(1.90)	(1.28)	(1.95)	(2.73)	(0.76)	(0.53)	(3.53)	(3.72)	(2.03)	(1.95)	(2.19)	(1.90)
SEX	−.066	−.003	−.118	−.012	.178	.014	−.152	−.019	−.122	−.017	−.273	−.024
	(−0.50)	(−0.22)	(−0.53)	(−0.63)	(1.16)	(0.91)	(−.97)	(−1.04)	(−0.93)	(−1.05)	(−1.66)	(−1.44)
F 15–44	.850	.070	1.175	.106	.399	.036	1.24	.152	1.11	.134	1.277	.111
	(3.93)	(3.19)	(3.84)	(3.96)	(1.63)	(1.44)	(5.36)	(5.72)	(5.22)	(4.95)	(5.01)	(4.37)
FAMSZ	.0005	−.0004	.037	.004	.011	.001	−.044	−.003	−.014	−.001	−.003	−.005
	(0.02)	(−0.11)	(0.86)	(0.90)	(0.31)	(0.37)	(−1.30)	(−0.78)	(−0.48)	(−0.28)	(−0.07)	(−0.13)
WORKING	−.263	−.032	−.572	−.067	−.307	−.034	−.342	−.054	−.324	−.058	−.521	−.079
	(−2.07)	(−2.29)	(−3.04)	(−3.61)	(−2.15)	(−2.19)	(−2.35)	(−2.82)	(−2.62)	(−3.46)	(−3.42)	(−4.46)
NOINS	.361	−.021	.072	−.009	.261	−.207	—	—	.330	−.039	—	—
	(2.38)	(−1.46)	(0.26)	(−0.37)	(1.59)	(1.27)	—	—	(2.47)	(2.46)	—	—
FAMINC	−.00004	.00002	−.0004	−.0	.001	.0001	.0004	−.0	.003	.0004	−.0005	−.0001
	(−0.04)	(0.17)	(−0.40)	(−0.02)	(0.68)	(0.83)	(0.48)	(−0.02)	(2.15)	(2.18)	(−0.53)	(0.53)
GP/MD	−4.13	−.506	−6.240	−.428	1.18	.126	1.61	.201	.503	.038	.161	.014
	(−1.74)	(−2.06)	(−2.35)	(−1.73)	(0.89)	(0.96)	(1.24)	(1.34)	(0.08)	(0.49)	(0.23)	(0.19)

Table 6.1—*continued*

Independent Variable or Statistic	Regression Coefficients (t statistics in parentheses)											
	22 Largest SMSAs				Other SMSAs				Nonmetropolitan Areas			
	Low Head Education		High Head Education		Low Head Education		Education High Head		Low Head Education		High Head Education	
	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS
SURG/MD	−7.35	−.738	−10.56	−.823	4.09	.410	4.82	.503	.372	.129	−1.297	−.117
	(−1.45)	(−1.43)	(−1.75)	(−1.49)	(1.61)	(1.55)	(1.91)	(1.90)	(0.35)	(0.96)	(−0.99)	(−0.83)
POPDENS	.002	.0002	.002	−.0004	.017	.002	−.007	−.0005	.078	.018	−.007	.004
	(0.26)	(0.42)	(0.17)	(−0.03)	(1.06)	(0.97)	(−0.50)	(−0.33)	(2.20)	(2.09)	(−0.17)	(0.11)
MDFEE	−.161	−.019	−.063	−.002	−.013	−.001	.042	−.005	−.065	−.005	.035	.003
	(−2.31)	(−2.54)	(−0.61)	(−0.15)	(−0.34)	(−0.03)	(1.26)	(−1.50)	(−1.45)	(0.99)	(0.98)	(0.73)
HOSCOST	.008	—	.002	—	.0003	−.0003	.008	.0007	−.003	−.0004	.003	.0005
	(1.30)	—	(0.22)	—	(−0.04)	(−0.45)	(1.55)	(1.56)	(−0.57)	(−0.52)	(0.62)	(0.80)
BEDS*	1.39	.104	.965	.039	.926	.062	.729	.102	.264	.015	1.152	.133
	(1.21)	(0.83)	(0.69)	(0.30)	(1.43)	(0.88)	(1.12)	(1.50)	(0.79)	(0.34)	(3.37)	(3.60)
HBMD*	−1.44	−.298	−10.67	−.105	.713	.004	−1.36	−.170	−2.07	−.178	−2.65	−.309
	(−0.35)	(−0.68)	(−1.75)	(−1.99)	(0.70)	(0.01)	(−0.93)	(−0.55)	(−1.14)	(−0.84)	(−1.68)	(−1.77)
OBMD*	−2.26	−.418	−8.87	−1.20	−1.82	−.085	.759	.172	1.79	.151	−.69	−.051
	(−0.47)	(−0.82)	(−1.39)	(−2.01)	(−0.54)	(−0.21)	(0.27)	(0.42)	(1.54)	(0.87)	(−0.85)	(−0.67)
Constant	.286	.499	3.01	.572	−5.29	−.130	−6.49	−.133	−3.27	.011	−3.25	.048
	(0.09)	(1.57)	(0.92)	(1.88)	(−3.26)	(−0.76)	(−4.26)	(−1.93)	(−4.12)	(0.11)	(−3.97)	(0.55)
$\bar{R}^2$ or significance of Chi-square statistic	.000	.075	.000	.082	.000	.060	.000	.082	.000	.098	.000	.057
n	4985	4985	2683	2683	3811	3811	3942	3942	4639	4639	3155	3155
F statistic for hypothesis of inequality of regression coefficients			1.95				1.56				1.51	
$F_{.01}$ (19, large n) = 1.88												
$F_{.05}$ (19, large n) = 1.57												

NOTE: Means and standard deviations are shown in appendix table 1.

multiple episodes, many had zero, and about 80% of those with some admissions had just one admission.

Admissions Rates

The effect of beds on hospital admissions per year is positive in all regressions, but is significant only for high education families in rural areas. F-tests indicate that the hypothesis of equality of the sets of regression coefficients across the education subsamples cannot be rejected at the 95% level for the rural and other metropolitan samples. The sets of coefficients are different for the large urban sample, but in that sample the coefficients on BEDS* do not differ significantly.[5] The results are therefore consistent with the hypothesis that an effect of availability of beds on use, if observed, should not be attributed to demand creation or information manipulation. Physician variables (OBMD* and HBMD*) more frequently have a negative than a positive effect on use, but are significant only for the high education persons in large cities in the OLS regression. As discussed in chapter 5, physician variables for this subsample have a significant negative effect on the use of ambulatory physicians' services as well.

Physician and hospital prices frequently have a negative effect on use, as does the absence of insurance coverage, but these variables are significant only for a few of the subsamples. The composition of the physician stock (GP/MD and SURG/MD) has no consistent effect on use of hospitals. Finally, variables measuring health status, work status, age, and female of childbearing age are almost always significantly related to use in the expected directions.

To summarize: availability variables generally have little consistent or significant effect on admission rates in these educational subgroups. The question of the effect of availability variables on total hospital admissions will be discussed in more detail below. These results for the subgroups do suggest, however, that the primary determinant of use is the health status of individuals, *not* the availability of beds or physicians.

Length of Stay

The results for length of stay, shown in table 6.2, display a similar pattern. Stay is more frequently positively related to beds, but the effect is small and is significant only for the high education subgroup in smaller metropolitan areas. Stay tends to be shorter where physicians are more plentiful, perhaps because more physicians can monitor their hospitalized patients more closely. Gross prices and physician stock specialty composition are unrelated to length of stay, while the existence of insurance coverage has negative but inconsistent effects.

Patient characteristics variables have the expected effects on stay, although the effects of health status variables are estimated less pre-

Table 6.2 **Average Length of Stay Regressions, All Episodes (OLS)**

Independent Variable or Statistic	Regression Coefficients (*t* statistics in parentheses)					
	22 Largest SMSAs		Other SMSAs		Nonmetropolitan Areas	
	Low Head Education	High Head Education	Low Head Education	High Head Education	Low Head Education	High Head Education
Independent	Low Head	High Head	Low Head	High Head	Low Head	High Head
RAD	.107	−.306	.208	−.117	.254	.168
	(0.91)	(−1.40)	(0.28)	(−0.60)	(3.34)	(1.76)
CONDS	1.02	1.81	.757	−.42	.451	.035
	(2.17)	(2.02)	(0.80)	(0.64)	(1.70)	(0.07)
AGE LT 15	−6.74	−4.36	−2.29	−9.18	−2.02	−1.53
	(3.13)	(−1.28)	(−0.49)	(−2.99)	(−1.40)	(−0.82)
AGE 45–64	1.71	4.69	6.05	−1.26	2.50	2.26
	(0.86)	(1.29)	(1.51)	(0.45)	(2.08)	(1.26)
AGE 65+	−.151	1.80	12.92	4.76	2.34	5.76
	(−0.06)	(0.43)	(2.73)	(1.43)	(1.63)	(2.56)
SEX	−1.71	−3.61	−6.08	4.09	−1.70	−1.88
	(−1.36)	(−1.28)	(−2.18)	(2.02)	(−2.12)	(−1.42)
F 15–44	−2.81	−1.10	1.85	−10.6	−.614	.436
	(−1.33)	(−0.29)	(0.41)	(−3.38)	(−0.44)	(0.22)
FAMSZ	.170	−.848	.457	.232	.154	−.274
	(0.53)	(−1.66)	(0.64)	(.50)	(0.86)	(0.89)
WORKING	−2.93	−2.20	.378	−3.82	−.910	−1.75
	(2.72)	(−1.00)	(0.15)	(−2.04)	(−1.21)	(−1.54)
NOINS	4.41	5.72	−6.49	——	.909	——
	(2.99)	(1.95)	(−2.14)	——	(−1.08)	——
FAMINC	.004	−.002	.013	.004	−.0006	.007
	(0.42)	(−0.14)	(0.53)	(0.44)	(−0.07)	(1.03)
GP/MD	25.5	2.37	11.7	−24.20	.120	5.18
	(1.06)	(0.11)	(0.46)	(−1.43)	(0.03)	(0.97)
SURG/MD	29.1	−18.6	5.71	−38.2	1.74	1.38
	(0.54)	(0.28)	(0.12)	(−1.19)	(0.27)	(0.14)
POPDENS	−.026	.155	−.421	−.137	−.043	−.038
	(−0.18)	(1.02)	(−1.26)	(−0.70)	(−0.23)	(−0.11)
MDFEE	.410	.015	.692	1.24	−0.11	.216
	(0.62)	(0.06)	(0.83)	(3.15)	(−0.40)	(0.80)
HOSCOST	.024	.046	−.134	−.083	−.012	.001
	(0.39)	(0.48)	(−1.17)	(−1.22)	(−0.43)	(0.22)
BEDS*	9.88	−8.19	−1.77	20.8	−2.77	1.20
	(0.85)	(−0.50)	(−0.14)	(2.36)	(−1.32)	(0.45)
HBMD*	77.7	−38.1	95.9	−.959	6.48	4.01
	(1.93)	(0.43)	(1.90)	(−0.02)	(0.53)	(0.33)
OBMD*	−38.1	−110.5	−81.9	−51.5	1.90	1.73
	(−0.80)	(1.63)	(−1.13)	(−1.2)	(0.32)	(0.24)
Constant	−11.44	2.12	17.33	21.8	6.68	.902
	(−0.36)	(0.04)	(0.54)	(1.1)	(1.37)	(0.13)
$\bar{R}^2$	.092	.064	.043	.123	.100	.064

Table 6.2—*continued*

Independent Variable or Statistic	Regression Coefficients (t statistics in parentheses): 22 Largest SMSAs, Low Head Education	22 Largest SMSAs, High Head Education	Other SMSAs, Low Head Education	Other SMSAs, High Head Education	Nonmetropolitan Areas, Low Head Education	Nonmetropolitan Areas, High Head Education
n	496	218	375	363	529	295
F statistic for hypothesis of inequality of regression coefficients		0.99		1.58		0.08
$F_{.05}$ (19, large n) = 1.57						

NOTE: Means and standard deviations are shown in appendix table 3.

cisely than in the other regressions. Children, women, and persons who are working tend to have shorter stays, and older persons longer ones.

Surgically Treated Hospital Episodes

It is widely believed that there is an "excess" of surgical specialists. While this definition is usually based on technical notions of how much work a surgeon can do, rather than on behavioral notions of how much work the surgeon is willing to do, one can interpret it as suggesting that there is an excess supply of surgeons' services. It will therefore be desirable to see whether the amount of in-hospital surgery (measured by the number of surgically treated hospital episodes, other than those for delivery) is related, *ceteris paribus*, to the stock of surgical specialists available to perform surgery.

Table 6.3 indicates the results of regressions of surgically treated hospital episodes using the same set of variables as before, except that SURG/MD has been deleted and surgical specialists per capita (SURG*) has been substituted for office based physicians per capita. The results for surgical episodes are similar to those obtained in the analysis of all hospital episodes. Hospital beds tend to be related positively to use, but the effect is not very strong nor is it measured very precisely; as in the case of all hospital episodes, it is significant only for high education families in rural areas. Physician stock specialty composition and gross price are not strongly related to the use of surgery. What is perhaps most striking is the finding that the number of surgical specialists per capita is not significantly related to the amount of surgery for any of the education-location subgroups. Indeed, the coefficient on this variable is negative in five out of six regressions. While these insignificant effects

Table 6.3 **Surgically Treated Hospital Episode Regressions Except Episodes for Normal Delivery: Tobit and OLS Procedures**

Independent Variable or Statistic	Regression Coefficients (t statistics in parentheses)											
	22 Largest SMSAs				Other SMSAs				Nonmetropolitan Areas			
	Low Head Education		High Head Education		Low Head Education		High Head Education		Low Head Education		High Head Education	
	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS
RAD	.111	.013	.143	.016	.145	.018	.131	.017	.116	.015	.080	.010
	(5.55)	(8.39)	(4.47)	(7.38)	(6.40)	(10.0)	(4.28)	(6.74)	(5.54)	(8.25)	(2.22)	(3.74)
CONDS	.330	.024	.325	.012	.245	.011	.494	.032	.348	.026	.374	.024
	(4.85)	(5.49)	(3.22)	(2.37)	(3.14)	(2.19)	(5.89)	(6.26)	(5.37)	(5.71)	(4.39)	(4.46)
AGE LT 15	−.001	−.004	−.413	−.017	−.304	−.013	−.062	−.005	−.475	−.023	−.021	−.008
	(−0.01)	(−0.29)	(−1.17)	(−1.18)	(−1.02)	(−0.90)	(−0.21)	(−0.34)	(−1.79)	(−1.66)	(−0.07)	(−0.53)
AGE 45–64	.304	.008	−.332	−.008	.127	.007	.398	.027	.216	.009	.846	.049
	(1.32)	(0.63)	(−.993)	(−0.62)	(.47)	(0.53)	(1.44)	(1.96)	(.94)	(0.67)	(2.93)	(3.24)
AGE 65+	.349	.009	.331	.027	.058	.0004	.413	.014	−.174	−.015	.637	.033
	(1.23)	(0.62)	(.713)	(1.26)	(.18)	(0.61)	(1.08)	(0.70)	(−.58)	(−0.87)	(1.58)	(1.49)
SEX	−.041	−.0004	.197	.004	.331	.013	−.193	−.012	.127	.006	−.189	−.009
	(−0.25)	(0.05)	(.714)	(0.33)	(1.74)	(1.34)	(−0.91)	(−1.17)	(.73)	(0.64)	(−0.88)	(−0.76)
F 15–44	.582	.023	.376	.024	.075	.007	.518	.021	.337	.020	.521	.018
	(2.14)	(1.56)	(.989)	(1.53)	(.24)	(0.46)	(1.66)	(1.33)	(1.23)	(1.30)	(1.55)	(1.04)
FAMSZ	.003	−.0005	−.035	−.002	−.011	−.001	−.018	−.002	.008	−.0002	−.007	−.0006
	(0.08)	(−0.24)	(−.625)	(−0.71)	(−.24)	(−0.53)	(−0.38)	(−0.69)	(.21)	(−0.08)	(−0.13)	(−0.21)
WORKING	.002	.0009	−.209	−.010	−.093	−.0006	−.249	−.017	−.063	−.006	−.280	−.022
	(0.01)	(0.95)	(−.853)	(−0.96)	(−.51)	(−0.06)	(−1.21)	(−1.58)	(−.39)	(−0.65)	(−1.29)	(−1.91)
NOINS	.378	−.009	−.313	.016	.397	−.018	—	—	.545	−.023	—	—
	(1.99)	(−0.99)	(−.972)	(1.16)	(1.84)	(1.76)	—	—	(2.97)	(−2.65)	—	—
FAMINC	.0002	.00	.00006	.00	.0008	.0001	.002	.00009	.004	.0003	.001	.00007
	(.143)	(0.41)	(0.06)	(0.06)	(0.50)	(0.62)	(1.79)	(1.61)	(2.83)	(2.93)	(1.26)	(1.17)
GP/MD	−.498	−.062	−.649	−.074	−1.32	−.035	−2.122	−.086	−.525	−.024	.915	.043
	(−.329)	(−0.72)	(−.298)	(−0.82)	(−1.13)	(−0.60)	(−1.85)	(−1.53)	(−1.13)	(−0.95)	(1.95)	(1.75)
POPDENS	.0004	.0002	.008	.0003	−.029	−.0009	.006	.0007	.108	.009	−.045	−.002
	(.044)	(0.40)	(.571)	(0.47)	(−1.40)	(−0.81)	(0.32)	(0.72)	(2.63)	(3.24)	(−0.70)	(−0.70)

Table 6.3—*continued*

Independent Variable or Statistic	Regression Coefficients (t statistics in parentheses)											
	22 Largest SMSAs				Other SMSAs				Nonmetropolitan Areas			
	Low Head Education		High Head Education		Low Head Education		High Head Education		Low Head Education		High Head Education	
	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS
MDFEE	−.003	−.008	−.002	−.003	.0009	−.001	.002	.0008	−.002	−.003	−.00003	−.0001
	(−3.000)	(−1.89)	(−1.000)	(−0.63)	(0.39)	(−0.44)	(1.20)	(0.35)	(0.81)	(−0.89)	(−0.02)	(−0.04)
HOSCOST	.007	.0006	−.011	−.002	−.008	−.0001	−.0001	.0001	−.002	−.002	.008	.0004
	(1.000)	(1.28)	(−1.100)	(−0.47)	(−1.2)	(−0.33)	(−0.02)	(0.29)	(−0.26)	(−0.36)	(1.05)	(0.94)
BEDS*	1.64	.094	−.251	−.030	.229	.016	.123	.004	.318	.011	1.01	.052
	(1.106)	(1.16)	(−.142)	(−0.41)	(0.27)	(0.34)	(0.13)	(0.08)	(0.70)	(0.43)	(2.15)	(2.12)
HBMD*	−3.11	.042	−3.16	−.091	−4.62	−.208	−1.83	−.032	−1.98	−.071	−.97	−.006
	(−.004)	(0.14)	(−.420)	(−0.29)	(1.13)	(−0.97)	(−0.37)	(−0.16)	(−0.83)	(−0.58)	(−0.46)	(−0.05)
SURG*	19.538	.832	15.296	−.317	−15.151	−.040	−2.025	−.039	−2.838	−.107	−1.770	−.090
	(.949)	(0.75)	(.513)	(−0.27)	(−1.17)	(−0.05)	(−0.17)	(−0.06)	(−0.43)	(−0.31)	(−0.44)	(−0.49)
Constant	−5.31	−.001	−2.17	.130	−3.03	.049	−4.36	.025	−4.10	.025	−5.24	−.025
	(−3.568)	(0.02)	(−1.198)	(1.61)	(−2.83)	(0.81)	(−4.6)	(0.48)	(−5.21)	(0.61)	(−7.05)	(−0.60)
$\bar{R}^2$ or significance of Chi-square statistic	.000	.036	.000	.035	.000	.039	.000	.034	.000	.042	.000	.024
n	4985	4985	2693	2693	3811	3811	3942	3942	4639	4639	3155	3155
F statistic for hypothesis of inequality of regression coefficients	1.02				2.11				2.10			
$F_{.01}$ (18, large n) = 1.88												

NOTE: Means and standard deviations are shown in appendix table 1.

could possibly be explained for persons living in rural areas by the fact that they may travel out of their primary sampling unit for care, very few of the persons in SMSAs are likely to leave the metropolitan area. In summary, the results do not differ across education subgroups, and are not even positive or significant. In view of these striking results (or nonresults), a more direct test of the existence of any availability effect for surgical services will be presented in the next section.

The effects of other independent variables on the use of surgery are similar to those in the overall hospital episodes regressions. Health status measures are strongly related to use: sicker people are more likely to have had surgery. Somewhat surprisingly, consumption of surgery tends to be highest, *ceteris paribus*, among the middle aged (45–64). There is a weak positive relationship between the frequency of surgery and females of childbearing age status, and a weak negative relationship with being employed. Insurance is fairly strongly related to the use of surgery for the lower education group, while family income is weakly related.

Availability Effects and the Use of Hospitals

The original hypothesis of the availability effect, often called Roemer's law, was derived from a study which found a positive relationship between the number of hospital beds and their use.[6] In a similar way, the notion that surgeons cause surgery is a strong point of health services research folklore, even though the results in the often-cited study by Lewis do not, in fact, provide very strong statistical support for the proposition.[7]

In the education-area subgroups investigated in this study, however, no such availability effects were found. F-tests shown in tables 6.1 to 6.3 indicate that, in many of the subsamples, it is preferable to permit the coefficients to differ by education subgroups. In principle, one should therefore test for the *overall* effect of any variable, such as BEDS* or SURG*, by including it interacting with the education dummies, and by interacting all other independent variables with those dummies. In practice, the large sample size makes such a procedure costly, and the results are often difficult to interpret in any case. As an alternative, we examined OLS regressions on data combined for all education groups within each area, as well as data aggregated over all areas. Dummies were introduced for education or location; no further interaction was attempted.

The results in table 6.4 do suggest that there is a weak effect of BEDS* on total admissions for the full sample (all education groups, all areas) even though the effect was not significant for the subsamples. Moreover, the magnitude of the effect is in any case quite small, with an elasticity of about 0.1. BEDS* has no overall effect on either length of stay or surgical admissions.

As before, we find that neither the surgeons per capita variable nor the other measures of physician stock are significant in any of the aggregated surgical episodes regressions. Physician stock and measures of the composition of physician stock likewise have no effects on total episodes or on length of stay. Physician availability does not belong in regressions describing hospital use.

An effect which does come through much more clearly in these aggregated samples is the effect of insurance on hospital use. Since almost all high education families have coverage, a no-insurance dummy was used to indicate only those low and middle education persons without coverage. For both total episodes and surgical episodes, there is a highly significant negative effect of lack of insurance coverage on use. The calculated admission rate for persons who lack insurance would be about 30 to 40% less than for persons with insurance. A somewhat surprising offset, however, is that persons with insurance tend to have significantly shorter stays than persons without insurance. The two effects nearly cancel out in terms of expected hospital days, although insurance coverage still probably has a positive effect on total expenditures.

Gross physician fees or hospital prices (which tend to be positively correlated) do not have a significant effect on total episodes, surgery, or length of stay. At a relatively low level of significance, there is a suggestion that high hospital prices reduce length of stay, while high surgical fees (especially in big cities) tend to discourage surgery. The results of these aggregate regressions are therefore roughly similar to those obtained from the disaggregated regressions. Availability effects on hospital use are small or nonexistent, and do not appear to arise from demand creation.

In particular, more surgeons do not mean more surgery. In contrast, a recent study by Fuchs, using the same data presented here but aggregating it into regional rates, presents the finding that surgeon availability is related to surgery rates, although the effect is relatively small (an elasticity of 0.3).[8] How can this finding be reconciled with those presented here?

There are two possibilities. First, this study has used many more personal characteristics, especially health status measures, than did Fuchs. While he did use *2SLS* and treat surgeon stock as endogenous, possible correlation (whether causal or not) between health status variables and the variables used to predict surgeon stock could lead to the finding of a spurious effect.

Second, there is a potentially important group of consumers which was not included in this sample, but was included in the calculations of

Table 6.4 **Aggregated Sample Regressions: Hospital Episodes, Length of Stay, and Surgically Treated Episodes (OLS)**

Independent Variable or Statistic	Regression Coefficients (t statistics in parentheses)											
	All Episodes				Surgically Treated Episodes				Average Length of Stay			
	22 Large SMSAs	Other SMSAs	Non-metro Areas	All Areas	22 Large SMSAs	Other SMSAs	Non-metro Areas	All Areas	22 Large SMSAs	Other SMSAs	Non-metro Areas	All Areas
RAD	.028	.026	.034	.029	.015	.015	.014	.015	.125	.196	.211	.167
	(19.3)	(14.3)	(18.0)	(29.8)	(14.7)	(12.7)	(12.18)	(23.0)	(1.68)	(1.78)	(3.35)	(3.51)
CONDS	.047	.046	.050	.048	.022	.019	.022	.021	1.15	.251	.392	.563
	(12.6)	(10.9)	(11.4)	(20.1)	(8.63)	(6.73)	(8.32)	(13.7)	(4.05)	(0.64)	(1.84)	(3.31)
AGE LT 15	−.044	−.036	−.045	−.042	.011	−.010	−.013	−.011	−5.96	−3.34	−2.89	−4.21
	(−4.03)	(−3.03)	(−3.44)	(−6.13)	(−1.45)	(−1.24)	(−1.60)	(−2.51)	(−4.78)	(−2.01)	(−2.94)	(−5.56)
AGE 45–64	.033	.028	.047	.036	.014	.014	.020	.016	.071	2.70	1.70	1.26
	(3.24)	(2.44)	(3.80)	(5.50)	(2.13)	(1.81)	(2.62)	(3.76)	(0.06)	(1.73)	(1.92)	(1.84)
AGE 65+	.036	.062	.060	.052	.007	.015	.006	.009	−.232	8.02	4.62	4.07
	(2.45)	(3.75)	(3.38)	(5.46)	(0.70)	(1.31)	(0.60)	(1.46)	(−0.16)	(4.23)	(4.09)	(4.71)
SEX	−.014	.005	−.021	−.010	−.004	.002	−.0008	−.001	−1.15	−1.47	−.822	−1.09
	(−1.75)	(0.56)	(−2.23)	(−2.07)	(−0.76)	(0.40)	(−0.14)	(−0.31)	(−1.35)	(−1.28)	(−1.25)	(−2.13)
F 15–44	.101	.078	.125	.100	.032	.020	.021	.025	−3.45	−2.01	−1.78	−2.54
	(8.45)	(5.90)	(8.63)	(13.3)	(4.04)	(2.29)	(2.42)	(5.07)	(−2.70)	(−1.18)	(−1.79)	(−3.30)
FAMSZ	.002	−.002	−.003	−.001	.0005	−.002	−.001	−.0008	−.207	.347	.095	.061
	(0.90)	(−1.03)	(−1.44)	(−0.92)	(0.44)	(−1.52)	(−1.01)	(−1.15)	(−1.15)	(1.28)	(0.67)	(0.54)
WORKING	−.054	−.033	−.053	−.047	−.011	−.002	−.006	−.007	−2.03	−1.08	−1.06	−1.35
	(−6.86)	(−3.91)	(−5.53)	(−9.53)	(−2.11)	(−0.31)	(−1.07)	(−2.11)	(−2.77)	(−1.12)	(−1.88)	(−3.08)
NOINS	−.018	−.034	−.037	−.030	−.020	−.021	−.020	−.021	2.37	3.56	1.02	2.25
	(−1.86)	(−3.15)	(−3.52)	(−5.02)	(−3.11)	(−2.95)	(−3.18)	(−5.51)	(2.33)	(2.60)	(1.47)	(3.84)
FAMINC	−.0001	.000	.00002	−.00003	−.00004	.00005	.0001	.00003	.004	.005	−.001	.003
	(−1.99)	(0.04)	(0.48)	(−0.80)	(−1.33)	(1.30)	(2.44)	(1.26)	(0.70)	(0.67)	(−0.21)	(1.02)
GP/MD	−.392	.002	.017	−.002	−.081	−.025	−.004	−.021	10.1	3.47	−.522	4.01
	(−3.17)	(1.01)	(0.40)	(−0.06)	(−1.71)	(−0.80)	(−0.30)	(−1.96)	(0.71)	(0.40)	(−0.19)	(1.36)
POPDENS	.003	−.0003	.004	−.0005	.0005	−.0003	.003	−.0003	.116	−.100	.131	.069
	(0.57)	(−0.36)	(1.53)	(−1.63)	(1.58)	(−0.55)	(2.00)	(−1.36)	(2.44)	(−0.84)	(0.82)	(2.49)

Table 6.4—*continued*

Independent Variable or Statistic	All Episodes: 22 Large SMSAs	All Episodes: Other SMSAs	All Episodes: Non-metro Areas	All Episodes: All Areas	Surgically Treated Episodes: 22 Large SMSAs	Surgically Treated Episodes: Other SMSAs	Surgically Treated Episodes: Non-metro Areas	Surgically Treated Episodes: All Areas	Average Length of Stay: 22 Large SMSAs	Average Length of Stay: Other SMSAs	Average Length of Stay: Non-metro Areas	Average Length of Stay: All Areas
	Regression Coefficients (t statistics in parentheses)											
MDFEE	−.010	.002	−.005	−.005	−.007	.0000	.0003	−.001	.009	.691	.016	.247
	(−2.49)	(1.03)	(−0.21)	(−0.37)	(−3.07)	(0.05)	(0.17)	(−1.17)	(0.02)	(2.66)	(0.09)	(1.88)
HOSCOST	.0008	−.000	−.002	.00004	.0002	−.0001	−.000	.0000	.010	−.069	−.003	−.036
	(2.16)	(−0.02)	(−0.59)	(0.26)	(0.69)	(−0.55)	(0.02)	(0.05)	(0.28)	(−1.76)	(−0.13)	(−2.05)
BEDS*	.021	.060	.028	.036	.057	−.014	.002	−.005	4.54	5.74	−.855	1.57
	(0.34)	(1.58)	(1.27)	(2.18)	(−1.40)	(−0.56)	(0.14)	(−0.50)	(0.79)	(1.23)	(−0.59)	(1.00)
HBMD*	−.580	−.578	−.100	−.099	−.047	.053	.018	.029	−6.42	44.8	4.99	8.88
	(−2.39)	(−0.33)	(−0.90)	(−1.26)	(−0.30)	(0.45)	(0.27)	(0.59)	(−0.26)	(2.16)	(0.65)	(1.17)
OBMD*	−.761	−.008	.044	−.004	—	—	—	—	−37.5	−41.9	−1.68	−6.42
	(−2.82)	(−0.04)	(0.71)	(−0.07)	—	—	—	—	(−1.43)	(−1.73)	(−0.45)	(−1.39)
SURG/MD	−.677	.115	.046	.029	−.230	−.042	.056	.016	19.0	−2.23	.264	8.53
or SURG*	(−2.49)	(0.82)	(0.60)	(0.50)	(−0.39)	(−0.10)	(0.42)	(0.14)	(0.70)	(−0.13)	(0.05)	(1.59)
LOED	.008	.002	.011	.014	.014	.004	.011	.010	.082	.049	−.628	−.106
	(0.90)	(0.19)	(1.79)	(2.47)	(2.16)	(0.60)	(1.79)	(2.67)	(0.80)	(0.04)	(−0.91)	(−0.19)
MIDED	.011	.010	.004	.012	.014	.008	.004	.009	−.933	−.470	.543	−.216
	(1.15)	(1.13)	(0.70)	(2.25)	(2.52)	(1.53)	(0.70)	(2.70)	(−1.02)	(−0.45)	(0.83)	(0.43)
SMMET	—	—	—	−.0008	—	—	—	.001	—	—	—	.229
	—	—	—	(−0.12)	—	—	—	(0.24)	—	—	—	(0.33)
RURAL	—	—	—	.016	—	—	—	.004	—	—	—	−1.64
	—	—	—	(1.64)	—	—	—	(0.55)	—	—	—	(−1.75)
Constant	.505	−.008	.062	.060	.133	.052	.017	0.044	1.68	6.09	6.86	3.88
	(3.19)	(−0.09)	(1.20)	(1.58)	(2.98)	(1.65)	(0.80)	(2.75)	(0.10)	(0.56)	(1.96)	(1.05)
$\bar{R}^2$	.077	.057	.078	.017	.037	.028	.032	.032	.087	.066	.087	.074
n	14887	13018	12760	40665	14887	13018	12760	40665	1369	1244	1352	3965

Fuchs' rates. This is the group of persons in families with incomes below a poverty line. They were deleted from our sample because many of them may have had Medicaid coverage not measured in our data set. One may speculate that availability effects might be concentrated among this group to an extent sufficient to lead to measurement of an overall availability effect. Since members of this group are especially likely to be in families with heads of low education, the possibility is especially likely.

In summary, it appears that there is little evidence of an overall availability effect for hospital episodes, whether surgically treated or not. With the possible exception of the very poor, physician stock is unrelated to patients' use of hospitals, and beds are only weakly related. It does not even appear that surgery is more frequent where surgical specialists are more common.