Input and Technology Choices in Regulated Industries: Evidence from the Health Care Sector

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This paper examines the implications of regulatory change for input mix and technology choices of regulated industries. We study the increase in the relative price of labor faced by U.S. hospitals that resulted from the move from full cost to partial cost reimbursement under the Medicare Prospective Payment System (PPS) reform. Using the interaction of hospitals' pre-PPS Medicare share of patient days with the introduction of PPS, we document substantial increases in capital-labor ratios and declines in labor inputs following PPS. Most interestingly, we find that PPS seems to have encouraged the adoption of a range of new medical technologies.

I. Introduction

There is broad agreement that differences in technology are essential for understanding productivity differences across nations, industries, and firms. Despite this agreement, we know relatively little about the empirical determinants of technology choices and of adoption of capital goods embodying new technologies. The lack of empirical knowledge is even more pronounced when we turn to regulated industries, such

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as health care, electricity, and telecommunications, which not only are important for their sizable contributions to total GDP but have been at the forefront of technological advances over the past several decades. In this paper, we investigate how input and technology choices respond to changes in the regulatory regime.

Starting in the mid-1980s, a number of different industries in a variety of countries experienced a change in the regulatory regime away from full cost reimbursement toward some type of "price cap."[1] These new regulatory regimes often entailed a mixture of "partial cost reimbursement" and "partial price cap." Under this mixed regime—which we refer to hereafter as "partial cost reimbursement"—only expenditures on capital inputs are reimbursed, whereas labor expenses are supposed to be covered by the fixed price paid per unit of output. Consequently, a change from full cost to partial cost reimbursement increases the relative price of labor inputs, among other things.

Despite many examples of this type of partial cost reimbursement, including the Medicare Prospective Payment System (PPS) reform in the United States, which we study in this paper, partial cost reimbursement has received little theoretical or empirical attention. For example, in his recent survey, Joskow (2005, 36) notes that "Although it is not discussed too much in the empirical literature, the development of the parameters of price cap mechanisms . . . [has] typically focused primarily on operating costs only, with capital cost allowances established through more traditional utility planning and cost-of-service regulatory accounting methods."

In this paper, we empirically investigate the impact of Medicare PPS in the United States. Introduced in October 1983, PPS changed reimbursement for hospital inpatient expenses of Medicare patients from full cost to partial cost reimbursement, resulting in significant changes in the relative factor prices faced by hospitals. The motivation behind the reform was to reduce the level and growth of hospital spending, which had been rising rapidly (as a share of GDP) for several decades.

We first present a simple neoclassical framework highlighting how the change in relative factor prices faced by hospitals should affect their demand for capital and labor and their technology adoption decisions.[2]

[1] Examples include the telecommunications sector in the United States and United Kingdom; gas, electric, and water utilities in the United Kingdom, New Zealand, Australia, and parts of Latin America (see, e.g., Laffont and Tirole 1993; Armstrong, Cowen, and Vickers 1994; Joskow 2005); and the Medicare Prospective Payment System for U.S. hospitals, which is the focus of this paper.

[2] Our framework is related to that of Averch and Johnson (1962) and Baumol and Klevorick (1970) but focuses on cost reimbursement rather than rate of return regulation and on the relative price changes implied by the switch from full cost reimbursement to partial cost reimbursement. More important, it derives the implications of the change in regulation regime on technology choices. These implications are not discussed either in

In terms of our framework, PPS increases the price of labor faced by hospitals but leaves the price of capital unchanged. Before PPS, hospitals were reimbursed retrospectively for capital and labor costs associated with the care of Medicare patients. The PPS reform left the reimbursement for capital unchanged while introducing prospective payments for labor. After PPS, hospitals bore the full marginal costs of labor inputs but received a fixed payment for each admitted Medicare patient, regardless of the actual labor costs incurred for that patient. We refer to this post-PPS fixed payment as a "price subsidy."

The increase in the price of labor faced by hospitals relative to the price of capital implies that PPS should increase the capital-labor ratio of hospitals. However, the impact of the change in regulation regime on labor inputs, capital inputs, and technology adoption decisions depends on the level of the price subsidy, the extent of decreasing returns to capital (or technology) and labor, and the elasticity of substitution between these factors. In practice, the price subsidy seems to have been limited, so that our theoretical framework suggests that the demand for labor should decline. Nevertheless, when there is sufficient substitution between capital (or technology) and labor, the demand for capital may increase. Intuitively, PPS, by making labor more costly, induces hospitals to downsize. In the standard case, with constant returns to scale to capital and labor, this will necessarily be associated with a decline in the demand for both labor and capital. However, with decreasing returns to scale and sufficient substitution between capital and labor, affected hospitals can increase rather than decrease their demand for capital. The same also applies for their technology decisions, so that PPS may induce more rapid adoption of new technologies, even as hospitals downsize.[3]

The PPS reform provides an attractive setting for studying the impact of regulatory change on firm input and technology choice for several reasons. First, the health care industry is one of the most technologically intensive and dynamic sectors in the United States. Indeed, rapid technological change is believed to be the major cause of both the dramatic increase in health spending as a share of GDP and the substantial health improvements experienced over the last half century (Newhouse 1992; Fuchs 1996; Cutler 2003). Understanding the determinants of technological progress in the health care sector, and the role played by

Averch and Johnson or Baumol and Klevorick or in the optimal regulation models (e.g., Laffont and Tirole 1993).

[3] This result also highlights a parallel between our simple framework and the labor push theory of innovation suggested by Hicks (1932) and Habakkuk (1962), where higher wages may encourage technology adoption. Note, however, that in our empirical setting, the introduction of PPS is associated with both an increase in the price of labor and some increase in the price of output (increased reimbursement provided per Medicare patient admitted). Our empirical results on the effect of PPS on technology adoption therefore do not provide direct evidence on the labor push theory.

government policy, is therefore of substantial interest in its own right. Second, government regulation is ubiquitous in this industry. Finally, because of substantial differences in the importance of Medicare patients for different hospitals, there is an attractive source of variation to determine the effects of such a regulatory reform on input and technology choices: hospitals with a higher Medicare share experience a larger increase in the relative price of labor from the PPS reform to reimbursement of Medicare patients.

Our empirical strategy is to exploit the interaction between the introduction of PPS and the pre-PPS share of Medicare patient days (*Medicare share* for short) in hospitals. We document that before the introduction of PPS, hospitals with different Medicare shares do not display systematically different trends in their input or technology choices. In contrast, following PPS, hospitals with different Medicare shares show significantly different trends.

Consistent with the predictions of our motivating theory, there is a significant and sizable increase in the capital-labor ratio of higher–Medicare share hospitals associated with the change from full cost to partial cost reimbursement. This change in the capital-labor ratio is made up of a decline in the labor inputs of higher–Medicare share hospitals, with approximately constant capital inputs. Perhaps most interestingly, we find that the introduction of PPS is associated with a significant increase in the adoption of a range of new health care technologies. We document this pattern both by looking at the total number of different technologies used by hospitals and also by estimating hazard models for a number of specific high-tech technologies that are in our sample throughout. The increase in technology adoption and the decline in labor inputs associated with the increase in the relative price of labor also suggests that there is a relatively high degree of substitution between technology and labor. We present suggestive evidence of one possible mechanism for this substitution: the introduction of PPS is associated with a decline in length of stay, which may represent substitution of high-tech capital equipment for relatively labor-intensive hospital stays.

Finally, we present evidence that the introduction of PPS is associated with an increase in the skill composition of hospital nurses. This pattern buttresses our results on increased capital-labor ratios and technology adoption, since the consensus view in the literature is that skilled labor is complementary to capital and/or technology (e.g., Griliches 1956; Berman, Bound, and Griliches 1994; Autor, Katz, and Krueger 1998; Krusell et al. 2000; Acemoglu 2002).

We consider a number of alternative interpretations for our findings and conclude that the evidence for them is not compelling. We therefore interpret our finding of PPS-induced changes in input mix and technology adoption in the health care sector to be a response to the changes in relative factor prices induced by the change in regulation regime. Consequently, to our knowledge, this makes ours the first paper to document that technology adoption in the health care sector is affected by relative factor prices.[4]

It is also noteworthy that our findings run counter to the general expectation that PPS would slow the growth of expensive technology diffusion (see, e.g., Sloan, Morrissey, and Valvona [1988], Weisbrod [1991], and the discussion of initial expectations in Coulam and Gaumer [1991]). However, most prior analyses of PPS have conceived of it as a move from full cost reimbursement to full price cap reimbursement and have overlooked the fact that it was only a partial price cap on noncapital expenditures; both our theoretical and empirical results show the importance of the increase in the relative price of labor resulting from the partial price cap structure.[5]

The rest of the paper proceeds as follows. Section II outlines a simple neoclassical model of regulation and the implications of the change in regulation regime on input and technology choices. Section III reviews the relevant institutional background on Medicare reimbursement. Section IV describes the data and presents some descriptive statistics. The econometric framework is presented in Section V. Our main empirical results are presented in Section VI, and Section VII shows that they are robust to a number of alternative specifications. Section VIII briefly summarizes our findings and discusses some directions for further work.

II. Motivating Theory

In this section, we discuss a simple neoclassical model of regulation and derive its implications for a switch from full to partial cost reimbursement. To conserve space, the claims made in this section are formalized and proved in online Appendix B.

As noted in the introduction, PPS corresponds to a switch from full retrospective cost reimbursement to partial cost reimbursement. Under

[4] In this respect, our paper is related to the paper by Newell, Jaffe, and Stavins (1999), who study the effect of energy price increases on the energy efficiency of a variety of appliances. See also Greenstone (2002) on the effect of environmental regulations on plant-level investment. In the hospital sector, past work has suggested that hospital technology adoption appears to increase in response to traditional fee-for-service health insurance (Finkelstein 2007) and to slow in response to managed care organizations (Cutler and Sheiner 1998; Baker 2001; Baker and Phibbs 2002). In the context of the health sector more generally, the rate of pharmaceutical innovation appears to increase in response to increased (expected) market size (Acemoglu and Linn 2004; Finkelstein 2004) or to tax subsidies for R&D (Yin 2005). Also related to our paper is the paper by Cawley, Grabowski, and Hirth (2006), who study capital-labor substitution in nursing homes in response to relative factor prices.

[5] The literature on PPS is reviewed in Sec. III.

the partial cost reimbursement regime, capital costs associated with the care of Medicare patients are reimbursed retrospectively whereas labor expenses are reimbursed prospectively. Moreover, hospitals receive a fixed payment for each Medicare patient admitted in lieu of the direct reimbursement of actual labor costs incurred for the care of Medicare patients they previously received. We refer to this fixed payment as a "price subsidy" since it increased (from zero) the price Medicare paid hospitals for each patient; it could also be referred to as a "price cap" because the switch to PPS corresponds to partial price cap regulation. This new payment structure implies that under PPS, hospitals bear their own labor costs. In contrast, the reimbursement for capital expenses remains unchanged, so that at the margin, a hospital can still pass on additional capital costs associated with Medicare. Compared to the full retrospective reimbursement regime, this corresponds to an increase in the price of labor faced by hospitals relative to their capital costs.

To derive the implications of this change in regulation regime, we consider a stylized world in which hospitals maximize profits (and we ignore the interconnection between the demand for health care and various private and social insurance programs). Although nonprofit or public hospitals have other objectives as well, profit maximization both is a useful benchmark and also is consistent with a large empirical literature that finds essentially no evidence of differential behavior across for-profit and nonprofit hospitals (see Sloan [2000] for a recent review of this literature). Suppose that the revenue function of hospital i can be written as

$$\tilde{F}(A_i,\ L_i,\ K_i,\ z_i). \tag{1}$$

This function combines the production of health services by the hospital and the prices it faces for these services (which may be potentially affected by the supply by this hospital).[6] In (1), A_i is a one-dimensional index of technology determined by the technology adoption decisions of the hospital, L_i is total labor (which can further be divided into skilled and unskilled labor), and K_i is capital (including structures capital). Finally, z_i represents other inputs, in particular, managerial inputs and doctor services, which are typically not reported as part of hospital em-

[6] The composition of the patients of the hospital, in particular, between Medicare and non-Medicare patients, is also incorporated into this function (see online App. B). In practice, hospitals may not be able to choose the total number of Medicare patients. Either a hospital is the only one in the area, thus facing an essentially constant demand for Medicare services, or it may be competing with other hospitals in the area, in which case, the number of Medicare patients will depend on the quality of service. This would require a more involved analysis in which the firm chooses both quantity and quality, and there is quality competition. Although we believe that this is an important area for theoretical analysis, it falls outside the scope of our paper.

ployment. Throughout, we assume that $\tilde{F}$ is homothetic and exhibits "decreasing returns" to labor and capital (and also to labor and technology). This implies, for example, that when labor inputs and capital inputs are doubled, hospital revenues will increase less than twofold.

We also assume that hospitals are price takers in input markets, facing a wage rate of w per unit of labor and a cost of capital equal to R per unit of capital.[7] To simplify the discussion, let us also make two further assumptions in the text. First, at the margin there is fungibility between labor and capital inputs used for Medicare and non-Medicare purposes. Second, the Medicare share of the patients of a hospital, m_i, is exogenous. Online Appendix B shows how the results discussed here generalize when these assumptions are relaxed (so that the Medicare share of patients changes endogenously and there is only limited fungibility between Medicare and non-Medicare expenses).

The implications of the switch to partial cost reimbursement for input mix and technology can be derived simply by considering the profit maximization (cost minimization) of a hospital with a given Medicare share m_i and investigating how its decisions change in response to an increase in the relative price of labor w and how this response depends on m_i.

RESULT 1. The switch to partial cost reimbursement increases the capital-labor ratio, and this effect should be stronger for hospitals with a greater Medicare share.

This result is straightforward and follows simply from the cost minimization of a firm faced with a change in relative factor prices; the magnitude of the change in relative factor prices is increasing in the hospital's Medicare share since it is only reimbursement of Medicare patients that is affected.

Less obvious are the implications for the level of input demands. These depend on the generosity of the price subsidy introduced by partial cost reimbursement in lieu of the direct reimbursement of labor costs. If the price subsidy is sufficiently generous, high–Medicare share firms may expand their scale because of the greater profitability of their activities or they may try to attract more Medicare patients. In contrast, if the price subsidy is sufficiently low, then the switch to partial cost reimbursement approximates a pure increase in the price of labor, with no compensating increase in the price of "output." The preexisting evidence suggests that this latter case is likely to be more relevant in

[7] In practice, certain hospitals might have monopsony power for some component of their labor demand. For example, Staiger, Spetz, and Phibbs (1999) find evidence of hospital monopsony power in the market for registered nurses. Incorporating any such monopsony power would have no effect on our main results.

practice.[8] Also consistent with a relatively low price subsidy, our empirical work below shows that the price subsidy appears to have been less than sufficient to overturn the effects of decreased cost subsidies.

The next result summarizes the implications of the switch to partial cost reimbursement for the levels of input demand when the price subsidy is sufficiently low.

Result 2*a*. When the price subsidy in the partial reimbursement scheme is sufficiently low, the switch to partial cost reimbursement reduces labor demand. This decline is greater for hospitals with a greater Medicare share.

Result 2*b*. Moreover, if the (local) elasticity of substitution between capital (respectively, technology) and labor is sufficiently large, then the switch to partial cost reimbursement increases the demand for capital (respectively, technology). This increase is greater for hospitals with a greater Medicare share.

The most notable feature here is that the demand for capital (or technology) can increase even though labor demand decreases. The decrease in labor demand is intuitive in view of the fact that the price subsidy is limited, so that the switch to partial cost reimbursement approximates an increase in the price of labor, with the price of capital and the price of "output" remaining constant. Consequently, the greater price of labor (with limited price subsidies) induces hospitals to downsize and reduce employment. If, in addition, there were constant returns to scale to capital and labor, the decline in labor demand would be associated with a decline in the demand for capital. This standard result does not necessarily apply, however, when there are decreasing returns to capital and labor, as we have assumed above, and when there is sufficient substitutability between capital and labor. In this case, the greater labor costs resulting from the change in regulation regime may induce hospitals to substitute capital for labor with only limited change in their scale and revenues, thus increasing their overall demand for capital.

The same analysis establishes an analogous relationship between Medicare share and technology adoption. For concreteness, suppose that technology is embodied in equipment capital and recall that there are decreasing returns to technology and labor, in the sense that a doubling of equipment capital and labor leads to a less than twofold increase in output. In addition, define the elasticity of substitution between technology and labor analogously to the elasticity of substitution between

[8] Qualitative descriptions of the PPS suggest a relatively low level of the price subsidy, particularly after the first year of the program (Coulam and Gaumer 1991). The empirical evidence reviewed by Cutler and Zeckhauser (2000) and Coulam and Gaumer (1991) indicates that the introduction of PPS was associated with a decline in hospital profit margins, which is also consistent with a relatively low level of the price subsidy.

capital and labor (see online App. B). Then, result 2*b* also establishes that when there are decreasing returns to technology and labor and when the elasticity of substitution is sufficiently large, PPS can induce technology adoption. Intuitively, hospitals now substitute technology for labor, and this substitution can be sufficiently pronounced that hospitals may adopt new technologies even as they downsize.

We note that the effects on capital and technology need not be the same since the elasticities of substitution of each of these inputs with labor are not the same (e.g., structures capital may be more complementary to labor than labor-saving technology). Below, we will see that PPS appears to be associated with increased technology adoption combined with more or less constant overall capital expenditures, suggesting that there was likely a decline in some other type of capital expenditures, such as structures.

Finally, we also investigate the effect of the switch to partial cost reimbursement on the ratio of skilled to unskilled nurses. The following result summarizes the implications of this switch on the skill composition of employment.

Result 3. If there is technology-skill or capital-skill complementarity, then the switch to partial cost reimbursement will increase the ratio of skilled to unskilled workers. This effect will be stronger for hospitals with a greater Medicare share.

Since technology-skill and/or capital-skill complementarities appear to be a good approximation to the technology of many sectors, result 3 suggests that we may see a significant change in the skill composition of employment of affected hospitals and thus acts as a check on our capital-labor ratio and technology adoption results.

The above results take the Medicare share of patients in a hospital as given. In response to a switch to partial cost reimbursement, hospitals will also change the composition of their patients. Online Appendix B shows that when the price subsidy is low, there may also be a decline in the Medicare share of all hospitals, but this does not affect the results we focus on in our empirical analysis.

III. Overview of Medicare Reimbursement Policies

Medicare PPS was introduced in October 1983 (fiscal year 1984) in an attempt to slow the rapid growth of health care costs and Medicare spending. Under the original (pre-PPS) system of cost reimbursement, Medicare reimbursed hospitals for a share of their capital and labor inpatient expenses, which was proportionate to Medicare's share of patient days in the hospital (OTA 1984; Newhouse 2002, 22). By contrast, under PPS, hospitals are reimbursed a fixed amount for each patient based on his or her diagnosis, but not on the actual expenditures incurred on the patient. At a broad level, this reform can be thought of as a change from cost reimbursement to fixed price cap reimbursement, and indeed, it is often described in these terms (e.g., Cutler 1995).

However, an important but largely overlooked feature of the original PPS system—and a central part of our analysis—is that initially only the treatment of inpatient operating costs was changed to a prospective reimbursement basis. For the first 8 years of PPS, capital costs continued to be fully passed back to Medicare under the old cost-based reimbursement system, and capital reimbursement became fully prospective only in 2001. Thus for almost its first 20 years, PPS continued to reimburse capital costs at least partly on the margin.[9] The reason for the differential treatment of operating and capital costs, both in this case and more generally in other regulated industries, appears to be the greater difficulty in designing a prospective payment system for capital (CBO 1988; Cotterill 1991; Joskow 2005).

The PPS reform is thus an example of a switch from full cost reimbursement to partial cost reimbursement, as described in Section II. To our knowledge, this feature of PPS has received no theoretical or empirical attention, even though almost all empirical examinations of the impact of PPS focus on the initial PPS period when partial cost reimbursement was in effect.

Coulam and Gaumer (1991) and Cutler and Zeckhauser (2000) review the extensive empirical literature on the effects of PPS. Broadly speaking, this literature concludes that PPS was associated with declines in hospital spending and in Medicare utilization (both admissions and length of stay), but not with substantial adverse health outcomes. However, most of this literature is based on simple pre-post (time-series) comparisons. Important exceptions include Feder, Hadley, and Zuckerman's (1987) study of the impact of PPS on spending and Staiger and Gaumer's (1990) and Cutler's (1995) studies of the impact of PPS on health outcomes. Staiger and Gaumer pursue an empirical approach similar to our strategy below, which exploits the interaction between the introduction of PPS and hospital-level variation in the importance of Medicare patients. Our empirical findings below are consistent with the time-series evidence from this literature suggesting that there has been a decrease in hospital expenditures and in utilization associated with PPS. To our knowledge, our work is the first to investigate the impact

[9] The original legislation specified that the treatment of capital costs would be unchanged for the first 3 years of PPS (i.e., through October 1, 1986) and instructed the Department of Health and Human Services to study potential methods by which capital costs might be incorporated into a prospective payment system. In practice, a series of eleventh-hour delays postponed any change in Medicare's reimbursement for capital costs until October 1, 1991, at which point a 10-year transition to a fully prospective payment system for Medicare's share of inpatient capital costs began (GAO 1986; CBO 1988; Cotterill 1991).

of PPS on labor and capital inputs and the skill composition of the workforce.

Finally, a small empirical literature also uses pre-post comparisons to study the impact of PPS on technology adoption. This literature finds little conclusive evidence of any effect of PPS (PPAC 1988, 1990; Sloan et al. 1988). To our knowledge, ours is also the first theoretical or empirical study to show that PPS might have been associated with an overall increase in technology adoption.

IV. Data and Descriptive Statistics

A. *The AHA Data*

Our analysis of the impact of PPS uses seven years of panel data from the American Hospital Association's (AHA) annual census of U.S. hospitals. PPS took effect at the start of each hospital's fiscal year on or after October 1, 1983. Our data consist of 4 years prior to PPS (fiscal years 1980–83) and 3 years after PPS (fiscal years 1984–86). We interpret the year of the data as corresponding to the hospital's fiscal year.

We restrict our analysis to the first 3 years of PPS, during which the treatment of capital was specified in advance.[10] We also exclude from the analysis the four states (Maine, New York, Maryland, and New Jersey) that received waivers exempting them from the federal PPS legislation. Because these four states also experienced their own idiosyncratic changes in hospital reimbursement policy during our period of analysis (often right around the time of the enactment of federal PPS), the states are not useful for us as controls (HCFA 1986, 1987; Antos 1993). These four states contain about 10 percent of the nation's hospitals, leaving us with a sample of about 6,200 hospitals per year.

The data contain information on total input expenditures and its components, employment and its components, and a series of binary indicator variables for whether the hospital has a variety of different technologies. All these input and employment data refer to the total amounts for the hospital and therefore are unaffected by any potential reallocation of factor usage within the hospital, for example, to nursing home or outpatient units that may be affiliated with the hospital. In

[10] As explained in n. 9, the years following the initial 3-year period after the introduction of PPS were characterized by considerable uncertainty concerning the treatment of capital. Given this uncertainty, it is not ex ante clear how hospitals should be expected to behave. In light of this, we limited our main sample to include only the initial 3 years. Nevertheless, we also investigated how the capital-labor ratio and technology adoption changed in subsequent years. Our results (not reported) show that the increase in the capital-labor ratio and in technology adoption that we find below for the first 3 years persisted during the subsequent period of uncertainty (i.e., through 1990). These and other results mentioned in the paper but not shown in the tables are available on request from the authors.

addition, we also observe inpatient hospital utilization, specifically admissions and patient days. The expenditure and utilization data for year t are in principle measured for the 12-month reporting period from October 1, $t-1$, through September 30, t; the employment and technology variables are in principle measured as of September 30, t. Note that hospital employment and payrolls consist of nurses, technicians, therapists, administrators, and other support staff; most doctors are not included since they are not directly employed or paid by the hospital. With the exception of patient days, none of the variables are reported separately for Medicare. We use Medicare's share of patient days in the hospital as the key source of our cross-sectional variation in the impact of PPS across hospitals (see below).

Medicare explicitly defines a hospital's reimbursable capital costs to include interest and depreciation expenses (OTA 1984; GAO 1986; Cotterill 1991), each of which we can identify in the AHA data.[11] Since changes in interest expenses may reflect financing changes rather than real input changes, we focus on depreciation expenses (which are about two-thirds of combined interest and depreciation expenses). Medicare uses straight-line depreciation to reimburse hospitals for the depreciation costs of structures and equipment (CBO 1988). The estimated life of an asset is determined by the AHA; during the time period we study, it ranged from 4 to 40 years depending on the asset; lives of 5 and 10 years tend to be the most common (AHA 1983). Depreciation expenses therefore measure past and current capital expenditures rather than the capital stock (which would have been the ideal measure). Since the cost of capital and equipment prices should not vary systematically across hospitals with different Medicare shares, depreciation expenses should be a good proxy for the capital stock.

Our baseline measure of the capital-labor ratio, K_i/L_i in terms of the model, is therefore the "depreciation share," defined as depreciation expenses divided by operating expenses. We define operating expenses as total input expenses net of interest and depreciation expenses. Just under two-thirds of operating expenses are payroll expenses (including employee benefits), with the remainder consisting of supplies and purchased services. Although payroll expenses are a more direct measure of labor costs, they are not our preferred measure since they do not

[11] Capital-related insurance costs, property taxes, leases, rents, and return on equity (for investor-owned hospitals) are also included in capital costs. In practice, however, capital costs are primarily interest and depreciation expenses, which are also the items reported separately in the AHA data and used by the overseers of Medicare to study Medicare capital costs (e.g., CBO 1988; PPAC 1992, MedPAC 1999).

TABLE 1
Summary Statistics

Variable	Average	Standard Deviation
Medicare share of inpatient days in 1983 (m_i)	38%	21%
Real operating expenditures (000's)	\$30,976	\$44,539
Real depreciation expenditures (000's)	\$1,379	\$2,224
Depreciation share (depreciation/operating)	4.50%	2.50%
Skill ratio (RNs/RNs + LPNs)	70%	16%

Note.—The table reports averages for the various hospital characteristics. All dollar estimates are in thousands of 2004 dollars. All share estimates are multiplied by 100. The number of observations is 43,188, except for skill ratio, which is 43,162. Data consist of a total of 6,280 hospitals, of which 5,881 (94 percent) are in the data for all 7 years, and all are in the data for at least 2 years. All hospitals in the sample have information on Medicare share in 1983; this variable is defined as zero for hospitals that were exempted from the PPS reform (see the text for more details).

include the full set of costs that experienced the relative price change under PPS.[12]

Depreciation expenses are on average about 4.5 percent of operating expenses (see table 1), indicating that the hospital sector is much less capital intensive than many other regulated industries.[13]

B. *Descriptive Statistics and Time-Series Evidence*

Table 1 gives the basic descriptive statistics for our key variables over the entire sample. Changes in some of the outcome variables over time are depicted in figures 1–3.

Figure 1 shows the simple time-series average of hospitals' capital-labor ratio (depreciation share). Consistent with result 1, the time series displays a striking increase in the average capital-labor ratio at the time of PPS's introduction (fiscal year 1984) both in absolute terms and relative to the preexisting time-series pattern. Result 2 suggests that if the level of the price subsidy is sufficiently low, labor inputs should fall; but even in this case, capital inputs may rise or remain unchanged. Consistent with this, the time series shows a pronounced decrease in

[12] In practice, our results are not sensitive to alternative measures of capital or labor inputs, such as measuring labor inputs on the basis of payroll expenses or employment or measuring capital expenses on the basis of interest expenses or interest plus depreciation expenses (see Acemoglu and Finkelstein 2006).

[13] The National Income and Product Accounts indicate that the share of capital in value added in health services is 12.8 percent during the period of our data. In contrast, the share of capital in electric, gas, and sanitary services is 64.1 percent and in telephone and telegraph is 49 percent. We are grateful to Veronica Guerrieri for help with the National Income and Product Accounts.

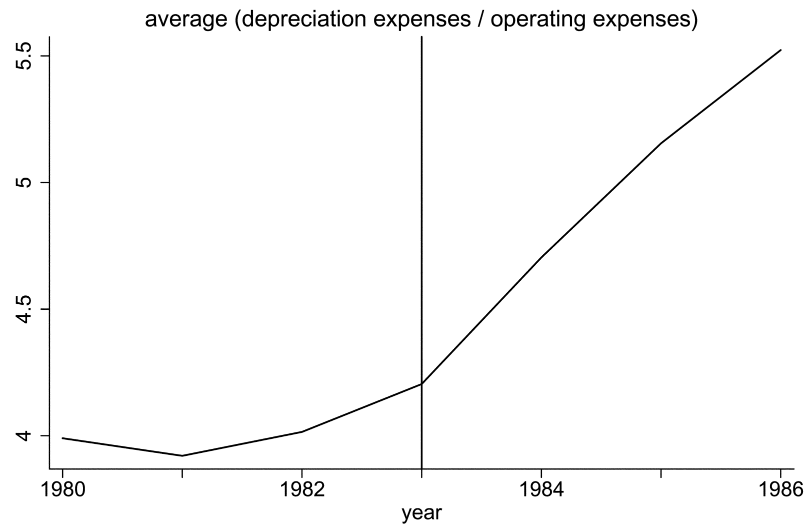

FIG. 1.—Capital-labor ratio (shown in units per 100)

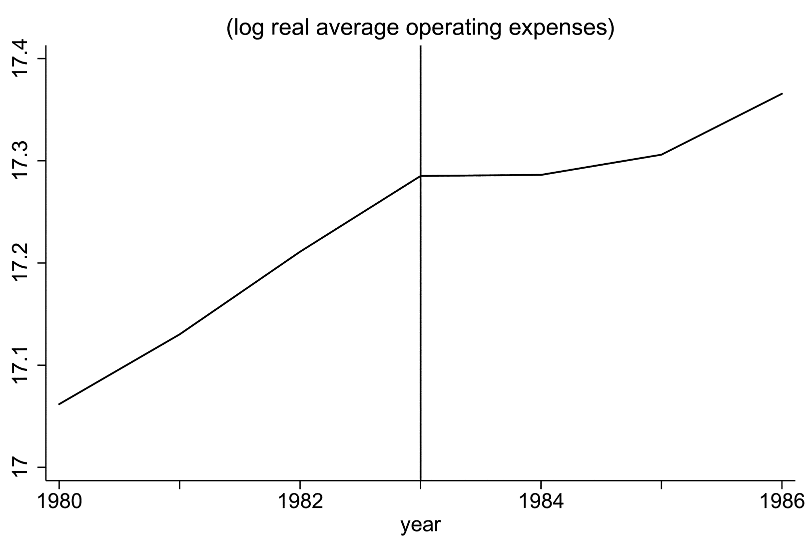

FIG. 2.—Log labor inputs (dollar amounts are measured in 2004 dollars)

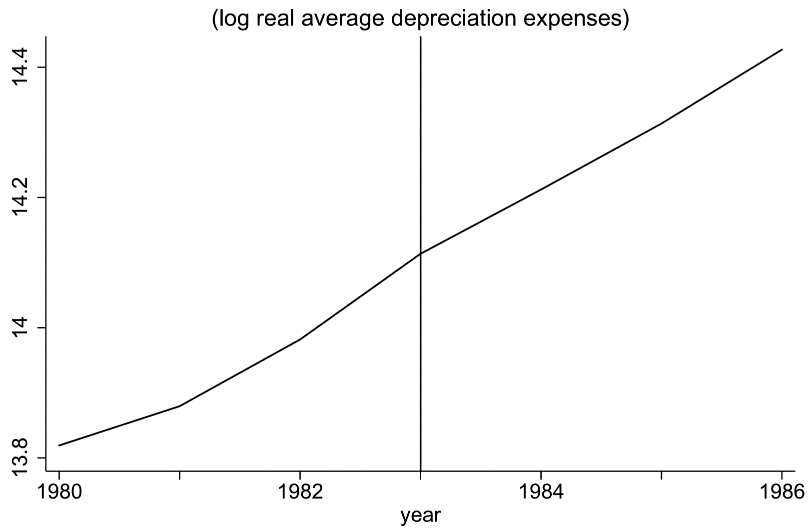

Fig. 3.—Log capital inputs (dollar amounts are measured in 2004 dollars)

labor inputs (real operating expenditures) relative to the preexisting trends (fig. 2). It also shows no evidence of a deviation in capital inputs (real depreciation expenditures) from the preexisting time-series trend (fig. 3).[14]

The time-series evidence is only suggestive, however, since it may be driven by other secular changes in the hospital sector or the macroeconomy more generally. Our empirical work below exploits the variation across hospitals in the impact of PPS focusing in particular on the interaction between the introduction of PPS and the hospital's pre-PPS Medicare share (the empirical counterpart of m_i in the model). It is nonetheless interesting that this very different empirical strategy will show patterns quite similar to those visible in figures 1–3.

V. Econometric Framework

As discussed in Section II, the impact of PPS on hospital input and technology choices should be larger for hospitals with a higher (pre-PPS) Medicare share, m_i. On the basis of this reasoning, our basic estimating equation is

$$y_{it} = \alpha_i + \gamma_t + \mathbf{X}'_{it} \cdot \boldsymbol{\eta} + \beta \cdot (\text{POST}_t \cdot m_i) + \varepsilon_{it}, \tag{2}$$

[14] To match the empirical work below, the time series in figs. 2 and 3 are presented on a log scale. In practice, the pattern is similar if we look at absolute levels.

where y_{it} is the outcome variable of interest in hospital i at time t. In our first empirical models, y_{it} will represent the capital-labor ratio (measured as the depreciation share) to investigate the predictions discussed in Section II. We will later use the same framework to investigate the responses of a number of other outcomes.

In our estimating equation (2), α_i represents a full set of hospital fixed effects, γ_t stands for a full set of year dummies, and $\mathbf{X}_{it}$ is a vector of other covariates, which are not included in the baseline regressions but will be added in several of the robustness checks below. Finally, ε_{it} is a random disturbance term capturing all omitted influences.

The main variable of interest is the interaction term $(\text{POST}_t \cdot m_i)$ with coefficient β. Here POST_t is a dummy variable that takes a value equal to one for the three post-PPS years (1984–86). A useful variant of this equation is

$$y_{it} = \alpha_i + \gamma_t + \mathbf{X}'_{it} \cdot \boldsymbol{\eta} + \beta \cdot (\text{POST}_t \cdot m_i) + \phi \cdot (d_{1983} \cdot m_i) + \varepsilon_{it}, \quad (3)$$

where d_{1983} is a dummy for the year 1983. The interaction term $d_{1983} \cdot m_i$ acts as a prespecification test; it will be informative on whether there are any differential trends in the variables of interest by Medicare share before the introduction of PPS.

We also estimate a more flexible version of these equations of the form

$$y_{it} = \alpha_i + \gamma_t + \mathbf{X}'_{it} \cdot \boldsymbol{\eta} + \sum_{t \geq 1981} \beta_t \cdot (d_t \cdot m_i) + \varepsilon_{it}, \quad (4)$$

where the term with the summation stands for a separate coefficient for 1981 and each subsequent year, and d_t is an indicator variable for year t. Relative to (2) or (3), the model in (4) allows both time-varying post-PPS effects and also a more flexible investigation of whether there are any differential trends in the variables of interest by Medicare share in any of the pre-PPS years.

In all models, to account for potential serial correlation of the observations from the same hospital, we adjust the standard errors by allowing for an arbitrary variance-covariance matrix within each hospital over time (see Wooldridge 2002, 275). In practice, this does not have much effect on the standard errors.

A key question is how to measure m_i empirically. Because reimbursement in the pre-PPS regime was based on Medicare's share of patient days in the hospital (Newhouse 2002, 22), we define m_i as the share of Medicare inpatient days. Since, as discussed in the motivating theory, the Medicare share m_i is likely to respond endogenously to the regulatory change, we measure m_i in 1983, the year prior to the implementation of PPS.

Figure 4 shows the considerable variation across hospitals in their

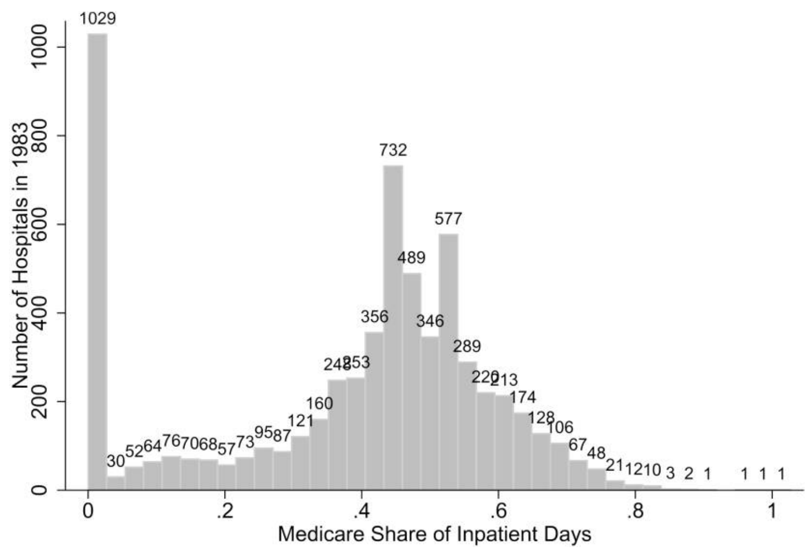

FIG. 4.—Distribution of hospitals by Medicare share in 1983

Medicare share in 1983. The average hospital's Medicare share is almost two-fifths (38 percent), with a standard deviation of over one-fifth (21 percent). The mass point of almost 15 percent of hospitals that we have coded as having a zero Medicare share reflects the fact that certain types of hospitals—specifically federal, long-term, psychiatric, children's, and rehabilitation hospitals—were exempt from Medicare PPS (OTA 1985; Newhouse 2002, 27). The exemption stems from the extremely low Medicare share of these hospitals. For our purposes, we code their m_i as zero since they would not be affected by the reform. In the robustness analysis below, we show that the main results can be obtained when we identify the effect of PPS using only the variation between zero share and nonzero share hospitals or using only the variation in m_i among hospitals coded with a nonzero m_i.

The identifying assumption in estimating equations (2), (3), and (4) is that, without the introduction of PPS, hospitals with different m_i's would not have experienced differential changes in their outcomes in the post-PPS period. However, m_i is not randomly assigned. For example, when we examine the variables summarized in table 1, we find that in the cross section prior to PPS (i.e., in 1983), a higher Medicare share m_i is correlated with lower operating expenses, a higher depreciation share, and a lower skill ratio. Any fixed differences across hospitals will be absorbed by the hospital fixed effects, the α_i's. However, such systematic differences raise concerns about whether, without the introduction of PPS in fiscal year 1984, hospitals with a different m_i would have experienced similar changes in the outcomes of interest. Equations (3) and (4) allow us to use the pre-PPS data to investigate the validity of this identifying assumption by looking for differential trends prior to PPS. The results below will show little evidence of such preexisting trends, supporting our identifying assumption.

Motivated by the theoretical predictions, we estimate equations (2), (3), and (4) for various dependent variables: capital-labor ratio (depreciation share), log labor inputs (log operating expenditures), log capital inputs (log depreciation expenditures), Medicare share of patient days, log average length of hospital stay, and the share of nurse employment that is high-skill. When the dependent variable is not already a share, we estimate the equation in logs.[15]

VI. Main Results

A. *Results on Capital-Labor Ratio*

Result 1 in Section II suggests that the move from full cost to partial cost reimbursement should increase the capital-labor ratio. We investigate this in table 2, which shows that the introduction of Medicare PPS is associated with a statistically and economically significant increase in the capital-labor ratio (depreciation share).

Column 1 shows the estimation of our most parsimonious equation, (2). The POST_t variable is simply a dummy for the 3 years in which PPS is in effect in our sample (1984–86). In this specification, the coefficient β on the key interaction term ($m_i \cdot \mathrm{POST}_t$) is estimated as 1.129 (standard error $=$ 0.108). This is both a highly statistically significant and economically large effect. Given that the average hospital has a 38 percent Medicare share prior to PPS, this estimate suggests that in its first 3 years, the introduction of PPS was associated with an increase in the depreciation share of about 0.42 ($\simeq 1.129 \times 0.38$) for the average hospital. Since the average depreciation share is about 4.5, this corresponds to a sizable 10 percent increase in the capital-labor ratio of the average Medicare share hospital.

Column 2 investigates whether the differential growth in the capital-labor ratio between high– and low–Medicare share hospitals was present before the introduction of PPS by estimating equation (3). The estimate of the key parameter, β, is essentially unchanged, and the coefficient ϕ on the interaction between the 1983 dummy and the Medicare share ($d_{1983} \cdot m_i$) is very small (practically zero) and highly insignificant. This indicates that relative to the years 1980–82, hospitals with a larger m_i

[15] A level specification would constrain the outcomes of each hospital to grow by the same absolute amount within a year, which is inappropriate given the considerable variation in size across hospitals.

TABLE 2
THE IMPACT OF PPS ON THE CAPITAL-LABOR RATIO

	(1)	(2)	(3)	(4)	(5)
POST × m_i	1.129	1.122			
	(.108)	(.121)			
POSTTREND × m_i				.538	.532
				(.050)	(.053)
$d_{1981} \times m_i$			.153		
			(.114)		
$d_{1982} \times m_i$			−.388		
			(.131)		
$d_{1983} \times m_i$		−.028	−.109		−.060
		(.098)	(.136)		(.088)
$d_{1984} \times m_i$			.601		
			(.163)		
$d_{1985} \times m_i$			1.068		
			(.172)		
$d_{1986} \times m_i$			1.474		
			(.189)		

NOTE.—The dependent variable is depreciation share. The table reports results from estimating eqqs. (2)–(5) by ordinary least squares (OLS). All regressions include hospital and year fixed effects. The mean dependent variable is 4.5. POST is an indicator variable for the years 1984–86. The variable POSTTREND = 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986, respectively. The variable d_t is an indicator variable for year t. The variable m_i measures the Medicare share of the hospital's inpatient days in 1983. Standard errors are in parentheses. Standard errors are adjusted to allow for an arbitrary covariance matrix within each hospital over time. The number of observations is 43,188. In col. 3, the omitted category is $d_{1980} \times m_i$. To interpret the magnitudes, recall that the average Medicare share in 1983 is about two-fifths.

did not experience a statistically or economically significant change in their capital-labor ratio in 1983 (the year before PPS) relative to hospitals with a smaller m_i. This is supportive of the identifying assumption that without the introduction of PPS, hospitals with different Medicare shares would have experienced similar changes in their capital-labor ratios.

Column 3 shows the results from estimating the more flexible equation (4) in which each year dummy is interacted with the hospital's 1983 Medicare share; the omitted year is 1980. This allows a further investigation of the identifying assumption as well as an examination of the timing of the response to PPS. The results indicate that relative to their 1980 spending, hospitals with a larger Medicare share did not experience a significant change in their capital-labor ratio relative to hospitals with a smaller Medicare share in the pre-PPS year 1981 or 1983, but there is a one-time downward blip in 1982.[16] Thus, the pattern over all four pre-PPS years suggests that, if anything, the capital-labor ratio may have been declining in hospitals with a larger Medicare share relative to hospitals with a smaller Medicare share. There is a pronounced shift

[16] This 1-year blip in 1982 is not a major concern for our results. We show in Sec. VII that our results are robust to numerous alternative specifications that deal flexibly with potential mean reversion and to including a linear trend interacted with Medicare share. Moreover, our results are also robust to excluding the 1982 data from the analysis, with or without including a linear trend interacted with Medicare share (not shown).

in this pattern starting in 1984, the first year that PPS is in place. In this year, hospitals with a larger Medicare share experience a statistically significant increase in the capital-labor ratio relative to hospitals with a smaller Medicare share, confirming the results in the previous two columns.

In a pattern that will repeat itself for many of the other dependent variables that we analyze, the results in column 3 also indicate that the magnitude of the increase in the capital-labor ratio associated with PPS grows from 1984 to 1985 and again from 1985 to 1986. This likely reflects, at least in part, lags in the implementation of PPS both in actuality and as measured in our data. PPS was effective at the beginning of the hospital's fiscal year starting on or after October 1, 1983. Hospitals were therefore added to the new regime throughout its first year in operation, with some not entering the new system until midway or late in the 1984 calendar year (OTA 1985). Moreover, not all hospitals follow the AHA instructions to report data for year t for the 12-month period from October 1, $t-1$, to September 30, t; in any given year, about half appear to instead report data for the 12-month period corresponding to their fiscal year. This also contributes to a staggered implementation of PPS in the data. However, the fact that the increase in the size of the effect from 1984 to 1985 (i.e., from a year in which only some hospitals were fully under the system to a year in which all were) is quite similar to the increase in the size of the effect from 1985 to 1986 (two years in which all affected hospitals were under the system) suggests that lags in implementation alone cannot fully account for the time pattern we observe. Lags in the hospital response to the new reimbursement regime (perhaps due to adjustment costs) may have also played a role.

Whatever its underlying cause, the empirical evidence in column 3 that the impact of PPS appears to grow over time suggests that a more appropriate parameterization of the post-PPS period may be a trend rather than a single post-PPS dummy. This motivates yet another slight variation on our estimating equation,

$$y_{it} = \alpha_i + \gamma_t + \mathbf{X}'_{it} \cdot \boldsymbol{\eta} + \tilde{\beta} \cdot (\text{POSTTREND}_t \cdot m_i) + \phi \cdot (d_{1983} \cdot m_i) + \varepsilon_{it}, \tag{5}$$

which imposes that the post-PPS effects increase linearly.[17] This equation has the advantage of summarizing the post-PPS patterns more parsimoniously than equation (4).

Columns 4 and 5 estimate equation (5) with and without the prespec-

[17] More specifically, $\text{POSTTREND}_t = \sum_{t\geq 1984}(t-1983)$, so that following PPS there is a linear trend difference among hospitals with different Medicare shares.

TABLE 3
THE IMPACT OF PPS ON OTHER VARIABLES

	Log Labor Inputs (1)	Log Capital Inputs (2)	Medicare Share (3)	Log Length of Stay (4)	Skill Share of Nurse Employment (5)
POSTTREND × m_i	−.068	−.023	−.032	−.030	1.67
	(.008)	(.016)	(.003)	(.011)	(.272)
d_{1983} × m_i	.022	.049	−.002	.019	.876
	(.013)	(.039)	(.006)	(.015)	(.567)
Observations	43,188	40,888	36,611	36,609	43,162
Mean dependent variable	15.83	12.61	.38	2.16	70

NOTE.—The table reports results from estimating eq. (5) by OLS for the dependent variable indicated in the column heading. Specifically, the dependent variable is log operating expenses (col. 1); log depreciation expenses (col. 2); Medicare share of inpatient days (col. 3); log length of stay, with length of stay defined as patient days/admissions (col. 4); and the ratio of the number of full-time-equivalent RNs to the sum of full-time-equivalent RNs plus full-time-equivalent LPNs (col. 5). All regressions include hospital and year fixed effects. The variable POSTTREND = 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986, respectively. The variable d_t is an indicator variable for year t. In all columns but cols. 3 and 4, m_i measures the Medicare share of the hospital's inpatient days in 1983. In cols. 3 and 4, m_i measures the Medicare share of the hospital's inpatient days in 1980, and data from 1980 are excluded from the analysis. Note also that while we code the regressor m_i to be zero for the approximately 15 percent of hospitals that are exempt from PPS (see fig. 4), we allow the dependent variable Medicare share in col. 3 to take its actual value for all hospitals. Standard errors are in parentheses. Standard errors are adjusted to allow for an arbitrary covariance matrix within each hospital over time. To interpret the magnitudes, recall that the average Medicare share in 1983 is about two-fifths.

ification test term, $d_{1983} \cdot m_i$. In both cases, there is a very precisely estimated coefficient of β of about 0.53 (standard error approximately 0.05). In column 5 as in column 2, there is no evidence of a pre-PPS differential effect. With a calculation similar to that above, the estimate of 0.53 suggests that, in its first three years, PPS was associated, on average, with an approximately 4 percent per year increase in hospitals' capital-labor ratio.

Columns 1 and 2 of table 3 investigate changes in the demand for capital and labor separately. In the interest of brevity, table 3 reports only results from estimating equation (5).[18] Column 1 investigates the differential change in (log) labor inputs (log operating expenses) across hospitals with different pre-PPS Medicare shares. Consistent with result 2a, the results suggest that the move from full cost to partial cost reimbursement was associated with a decline in labor inputs; the estimate of β, the coefficient on the interaction term ($\text{POSTTREND}_t \cdot m_i$) in column 1, is −0.068 (standard error = 0.008). The coefficient on $d_{1983} \cdot m_i$ shows some evidence of a small and marginally statistically insignificant increase in labor inputs in more affected hospitals prior to PPS; although this may raise concerns about the potential for mean reversion that may contaminate our estimate of the impact of PPS,

[18] For all the outcomes examined in table 3, results from the other specifications shown in table 2 are similar and can be found in the working paper version of the paper (Acemoglu and Finkelstein 2006).

Section VII shows that the results are highly robust to a number of specifications that deal flexibly with mean reversion issues.

The results for log capital inputs (log depreciation expenses) in column 2 indicate essentially no statistical or substantive effect on capital inputs. This is again consistent with the implications summarized in result 2*b* that even when the price subsidy is low enough that labor inputs decline, capital inputs need not decrease and may in fact increase when there is sufficient substitutability between capital and labor.

Consistent with a low price subsidy, the time-series evidence also shows a decline in the average Medicare share of patient days across hospitals after the introduction of PPS (not shown). In addition, column 3 of table 3 shows that there is a more pronounced decline in Medicare's share of patient days in hospitals that initially had a higher Medicare share.[19] We did, however, confirm that hospitals that initially had a higher Medicare share also had a higher Medicare share after the introduction of PPS, so that the initially higher–Medicare share hospitals are the ones that would be the most affected by the policy.[20] (The remaining columns in table 3 are discussed below.)

B. Technology Adoption

The AHA data contain a series of binary indicators for whether the hospital has various "facilities," such as a blood bank, open-heart surgery facilities, computed tomography (CT) scanner, occupational therapy, genetic counseling, and neonatal intensive care. These data have been widely used to study technology adoption decisions in hospitals (e.g. Cutler and Sheiner 1998; Baker and Phibbs 2002; Finkelstein 2007). Since they contain only indicator variables for the presence or absence of various facilities, we cannot study upgrading of existing technology or the intensity of technology use, but we can study the technology adoption decision on the extensive margin.

Overall, during our time period, the AHA collects information on the presence of 113 different facilities. These are listed, together with their sample means and the years in which they are available, in Appendix table A1. On average, a given facility is reported in the data set for 4.6 out of the possible seven years; only one-quarter of the technologies are

[19] To prevent a mechanical correlation between the cross-sectional variation, m_i, and the dependent variable, in col. 3 we define m_i on the basis of the hospital's Medicare share in 1980 and exclude 1980 from the analysis. All our previous results are robust to this alternative specification. Also, while we code the regressor m_i to be zero for the approximately 15 percent of hospitals that are exempt from PPS, we allow the dependent variable in this case to take its actual value for all hospitals. On average over 1981–86, the dependent variable is 0.38; it is 0.09 (0.43) for exempt (nonexempt) hospitals.

[20] In particular, the Spearman rank correlation between Medicare share in 1983 and the average Medicare share between 1984 and 1986 is 0.86.

in the data for all seven years. Moreover, as is readily apparent from Appendix table A1, the list encompasses a range of very different types of facilities. Given these two features of the data, we pursue two complementary approaches to analyzing the impact of the change from full to partial cost reimbursement on technology adoption.

Our first approach treats all facilities equally and estimates equations (2)–(5) using the (unweighted) number of facilities that hospital i has in year t as the dependent variable (in this specification, year fixed effects take care of the unbalanced panel nature of the technology data). This has the advantage of looking broadly across a wide range of different technologies but the disadvantage that it treats all the very different facilities symmetrically. This would be appropriate if all the technologies were perfect substitutes; this is the case in the model in online Appendix B, but may be far from reality. Our second approach therefore estimates separate hazard models of the time to adoption for specific "high-tech" technologies that are in the data for all the years of our sample.

In our first approach, the dependent variable is the raw count of the number of facilities of each hospital. This dependent variable ranges from zero to 77 with an average of 25. Approximately 10 percent of the hospital-years in the sample have zero facilities. The results are shown in table 4.[21] The estimates suggest that the change from full to partial cost reimbursement is associated with a statistically and economically significant increase in the number of hospital facilities. For example, the point estimate in column 1 is 2.622, suggesting that, on average, the regulatory change is associated with an increase of about one new facility ($\simeq 2.622 \times 0.38$) in a hospital over its first 3 years; this corresponds to about a 4 percent increase over the average number of facilities in a hospital (which is about 25).

The results are also broadly supportive of our identifying assumption of no differential trends across hospitals in the number of facilities prior to PPS. Column 3 shows some evidence of a differential decline in the number of facilities in higher–Medicare share hospitals in 1981 relative to 1980, but reassuringly, there is no similar pattern among any of the other pre-PPS years 1981, 1982, or 1983. Although the differential decline in 1981 may raise concerns about mean reversion, Section VII will show that the results are robust to several different checks against mean reversion.

One difference with the previous set of findings is the time pattern of the impact of PPS in the flexibly estimated specification (col. 3);

[21] Since there are a large number of zeros, we cannot estimate this equation in logs; nor is there a natural scaling factor to use in the denominator to turn this into a share estimate. Nevertheless, both the magnitude and the statistical significance of the estimates are robust to estimating a conditional fixed-effects Poisson model (Hausman, Hall, and Griliches 1984) instead. These results are shown in Acemoglu and Finkelstein (2006).

TABLE 4
The Impact of PPS on Technology Adoption I: Number of Facilities

	(1)	(2)	(3)	(4)	(5)
POST × m_i	2.622	2.501			
	(.357)	(.401)			
POSTTREND × m_i				1.156	1.094
				(.164)	(.177)
$d_{1981} \times m_i$			−2.423		
			(.526)		
$d_{1982} \times m_i$			−2.965		
			(.541)		
$d_{1983} \times m_i$		−.467	−2.281		−.631
		(.354)	(.517)		(.326)
$d_{1984} \times m_i$			−.496		
			(.567)		
$d_{1985} \times m_i$			1.894		
			(.634)		
$d_{1986} \times m_i$			.696		
			(.619)		

Note.—The dependent variable is number of facilities. All regressions include hospital and year fixed effects. The mean dependent variable is 25. The table shows results from estimating eqq. (2)–(5) by OLS. The variable POST is an indicator variable for the years 1984–86. The variable POSTTREND = 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986, respectively. The variable d_t is an indicator variable for year t. The variable m_i measures the Medicare share of the hospital's inpatient days in 1983. Standard errors are in parentheses. Standard errors are adjusted to allow for an arbitrary covariance matrix within each hospital over time. The number of observations is 43,188. In col. 3, the omitted category is $d_{1980} \times m_i$. To interpret the magnitudes, recall that the average Medicare share in 1983 is about two-fifths.

rather than the approximately linear growth for the other variables studied so far, the number of facilities in the affected hospitals shows a statistically significant increase from 1983 to 1984 and again from 1984 to 1985, but the effect then appears to decline somewhat from 1985 to 1986.

An important drawback to the preceding analysis is that it treats all technologies as perfect substitutes. As an alternative, we estimate separate hazard models of the time to adoption for specific technologies that are in the data for all the years of our sample. We focus on 10 technologies that were identified as high-tech by previous researchers (Cutler and Sheiner 1998; Baker 2001; Baker and Phibbs 2002) and that are present in our data in all years. Two of these are cardiac technologies (cardiac catheterization and open-heart surgery), two are diagnostic technologies (CT scanner and diagnostic radioisotope facility), four are radiation therapies used in cancer treatment (megavoltage radiation therapy, radioactive implants, therapeutic radioisotope facility, and x-ray radiation), and the remaining two are the neonatal intensive care unit and organ transplant. Figure 5 plots the diffusion pattern over our sample period of each of these 10 technologies; they differ both in their initial diffusion level and in whether and how rapidly they are diffusing over our sample period.

In the hazard model analysis, we exclude hospitals that have a given

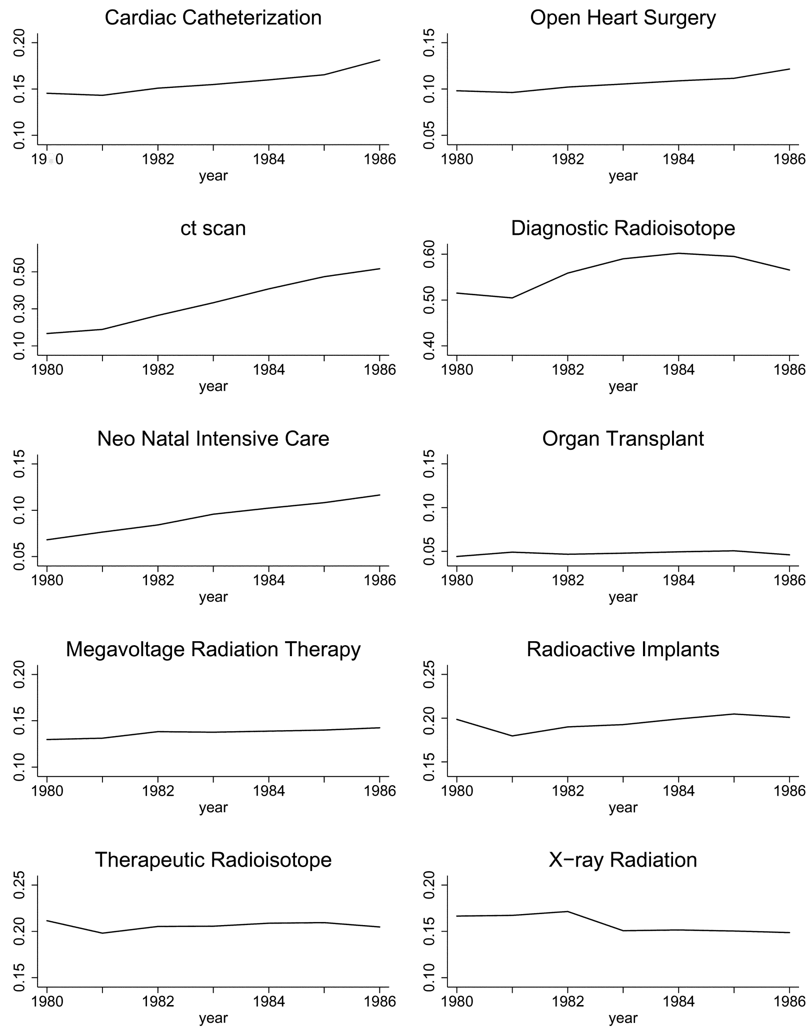

FIG. 5.—Technology diffusion

technology in 1980 (since they are not "at risk" of failure, i.e., of adoption) and treat hospitals that have still not adopted the technology by 1986 (the end of our sample period) as censored. Our first model is an exponential (i.e., constant baseline) proportional hazard model of the form

$$\lambda_t = \alpha \exp\left[\gamma_t + \phi \cdot d_{1983} \cdot m_i + \beta \cdot (\mathrm{POST}_t \cdot m_i) + \mathbf{X}_i' \cdot \boldsymbol{\eta}\right], \qquad (6)$$

where λ_t denotes the conditional probability that the hospital adopts the technology in question at time t, given that it has not yet adopted the technology, and α denotes the constant baseline hazard parameter (which we estimate). The assumption of the proportional hazard model is that the covariates shift the baseline hazard proportionally. Our second estimation strategy uses the Cox semiparametric proportional hazard model, which allows for a fully flexible, nonparametric baseline hazard λ_0 (see Kiefer 1988). In the Cox model, we do not include year fixed effects since the fully flexible baseline hazard is also specified with respect to calendar time.

Since we have at most a single transition (adoption) for each hospital, we cannot include hospital fixed effects in the hazard model analysis. Instead, we control for a range of time-invariant hospital characteristics (denoted by $\mathbf{X}_i$). These are m_i (i.e., the hospital's 1983 Medicare share), the square of m_i, the number of beds in 1983, and dummy variables for whether the hospital is a general (nonspecialty) hospital, whether it is a short-term (as opposed to a long-term) hospital, whether it is a federal hospital, whether it is located in an urban area, and a complete set of state fixed effects. The results reported so far are very similar if we control for these covariates instead of hospital fixed effects (not shown).

Table 5 reports the results from the exponential and Cox proportional hazard models. To conserve space, we report results only from a specification similar to equation (3), which includes a single interaction between the Medicare share, m_i, and the post-PPS period dummy, POST_t, as well as the prespecification test with the interaction between m_i and the dummy for the year 1983. Panel A reports results from the exponential proportional hazard model, and panel B reports results from the Cox proportional hazard model. For each technology in each panel, we report the coefficient and the standard error on $\text{POST}_t \cdot m_i$ and $d_{1983} \cdot m_i$. To illustrate the magnitude of our estimates, we also translate the hazard model coefficient on $\text{POST}_t \cdot m_i$ into the implied change in the proportion of hospitals that adopt the technology between 1981 and 1986 associated with changing m_i from zero to its mean value.

Since we look at 10 different technologies, the per-technology p-values will be lower than when each technology is viewed as part of a "family of hypotheses" that PPS had no effect on any of the 10 technologies. We therefore also report the family-wise error rate adjusted p-value (in brackets). This p-value corresponds to the probability of rejecting the null hypothesis of no effect on a given technology under the null family of hypotheses of no effect on any of the technologies.[22] The family-wise adjusted p-values are about five times larger than the standard p-values.

[22] We calculate these family-wise error rate adjusted p-values on the basis of 10,000 iterations of the free step-down resampling method of Westfall and Young (1993). This is more powerful than the standard Bonferroni correction because it does not assume independence across the 10 outcomes and sequentially removes hypotheses from the family

Both panels of table 5 show similar results and suggest that the shift from full cost to partial cost reimbursement was associated with increased technology adoption. At a 5 percent cutoff, the results from the exponential (respectively, Cox) model using the standard p-values suggest that PPS is associated with increased adoption of seven (respectively, six) of the 10 specific technologies. The results using the family-wise adjusted p-values suggest that PPS is associated with an increased adoption of three of the 10 technologies. Two of these three technologies, open-heart surgery and CT scan, are likely to be used disproportionately by Medicare patients. Our interpretation of the increase in adoption following PPS is thus along the lines of result 2b and relies on technology-labor substitution.[23]

While we cannot definitively pinpoint the mechanism for this technology-labor substitution, we can provide some evidence of one natural mechanism, the use of technology to reduce the length of stay. The typical hospital day is relatively nurse or custodial care intensive. By increasing the intensity of treatment up-front, hospitals may be able to reduce length of stay on the margin. Consistent with this, column 4 of table 3 presents evidence that Medicare PPS is associated with declines in log average length of stay, defined as log(patient days/admissions).[24]

It is also noteworthy that the other technology for which the family-wise adjusted p-values show a statistically significant increase in adoption is the neonatal intensive care unit (NICU), which is likely to be used almost exclusively by non-Medicare patients. Although an effect of PPS on NICU adoption may be viewed as problematic for our identification strategy, it is consistent with the growing body of evidence of "spillovers" in the health care sector.[25] Such spillovers could be incorporated into the framework in Section II by relaxing the assumption that z_i in the

after they are rejected. See Kling and Liebman (2004) for an application and a more detailed discussion of this method.

[23] As noted before, hospital labor consists of nurses, orderlies, administrators, and custodial staff but does not include doctors (who are neither employed by nor paid by the hospitals). Thus the technologies may well be complementary with physicians (or particular physician specialties) but still substitutes for hospital labor.

[24] Because (as in col. 3 of table 3) the dependent variable in col. 4 of table 3 is mechanically related to the cross-sectional variation of the Medicare share of patient days in 1983, we again drop 1980 from the sample and redefine the cross-sectional variation as the Medicare share of patient days in 1980.

[25] For example, Baicker and Staiger (2005) find that increases in the hospital reimbursement rate of Medicaid—which primarily reimburses for childbirth and pediatrics—are associated with declines not only in infant mortality but also in heart attack mortality among the elderly Medicare population. Similarly, Baker (1997) finds that higher managed care penetration in private insurance is associated with decreased hospital spending on fee-for-service Medicare patients. Most closely related to our findings, Dafny (2005) finds that in response to increases in average reimbursement rates for Medicare patients with specific diagnoses, hospitals spread the increased revenue uniformly across the treatment of all patients.

TABLE 5

THE IMPACT OF PPS ON TECHNOLOGY ADOPTION II: HAZARD MODELS OF TECHNOLOGY ADOPTION

	CARDIAC TECHNOLOGIES		DIAGNOSTIC RADIOLOGY		OTHER TECHNOLOGIES		RADIATION THERAPY (Cancer Treatment)			
	Cardiac Catheterization	Open-Heart Surgery	CT Scan	Diagnostic Radioisotope	Neonatal Intensive Care	Organ Transplant	Megavoltage Radiation Therapy	Radioactive Implants	Therapeutic Radioisotope Facility	X-Ray Radiation
	A. Exponential Proportional Hazard Model									
POST × m_i	1.23	2.61	.928	.666	3.83	1.74	1.76	−.74	−.096	−.081
	(.481)	(.683)	(.259)	(.265)	(.663)	(.785)	(.782)	(.508)	(.490)	(.601)
	[.071]	[.001]	[.003]	[.072]	[<.0001]	[.116]	[.116]	[.383]	[.975]	[.975]
d_{1983} × m_i	.24	1.48	.769	−.024	1.14	1.07	−1.397	−.72	.008	1.70
	(.692)	(1.054)	(.343)	(.312)	(.843)	(1.30)	(1.026)	(.769)	(.738)	(1.01)
	[.978]	[.745]	[.218]	[.996]	[.745]	[.885]	[.745]	[.883]	[.996]	[.584]
Change in % adopt if change POST × m_i from 0 to mean	.025	.004	.086	.054	.008	.003	.004	−.021	−.003	−.001

	B. Cox Proportional Hazard Model									
POST × m_i	1.13	2.48	.783	.577	3.69	1.61	1.69	−.826	−.183	−.188
	(.480)	(.680)	(.259)	(.266)	(.659)	(.783)	(.786)	(.511)	(.490)	(.601)
	[.129]	[.002]	[.024]	[.165]	[<.0001]	[.165]	[.165]	[.281]	[.921]	[.921]
d_{1983} × m_i	−.795	−.086	.204	−.659	.205	.023	−2.54	−1.598	−1.160	−.562
	(.510)	(.657)	(.300)	(.253)	(.641)	(.894)	(.725)	(.568)	(.513)	(.556)
	[.511]	[.984]	[.932]	[.070]	[.982]	[.984]	[.003]	[.040]	[.145]	[.838]
Change in % adopt if change POST × m_i from 0 to mean	.053	.053	.090	.088	.12	.016	.061	−.029	−.002	−.004
Mean adoption rate	.066	.033	.41	.36	.066	.040	.036	.082	.092	.073
Observations	4,861	5,130	4,739	2,758	5,301	5,437	4,950	4,542	4,485	4,741

NOTE.—The table shows coefficients from proportional hazard models. Censoring occurs if PPS has not been adopted by 1986. All estimates include covariates for the following hospital characteristics in 1983: Medicare share of patient days, Medicare share of patient days squared, number of beds, and indicator variables for state, whether in a metropolitan statistical area, whether a general hospital, whether a short-term hospital, and whether a federal hospital. Estimates using the exponential model also include year fixed effects. The variable POST is an indicator variable for the years 1984–86. The variable d_{1983} is an indicator variable for year 1983. The variable m_i measures the Medicare share of the hospital's inpatient days in 1983. "Change in % adopt if change POST × m_i from 0 to mean" denotes the difference in the average hospital adoption (by 1986) rate if all variables are set to their mean except for POST × m_i, which is set to zero, relative to if all variables (including POST × m_i) are set to their mean. Heteroskedasticity-robust standard errors are in parentheses. Family-wise adjusted p-values based on 10,000 iterations are in brackets (see the text for more details); these tend to be about five times larger than the unadjusted per-technology p-values (not shown). Number of observations denotes the size of the at-risk sample (i.e., the number of hospitals that have not adopted by 1980). Mean adoption rate denotes the percentage of the at-risk sample that adopted by 1986. This may differ slightly from the implied change in the proportion of hospitals that have the technology between 1980 and 1986 in fig. 5 because that figure is done in a cross section whereas the estimates in the table are done in a panel, and hospitals occasionally change their report from having to not having a technology; we have verified that the results in this table are robust to alternative ways of treating this measurement error.

production function (1) is constant. In this case, PPS-induced technology adoption may increase managerial effort (a component of z_i) that is complementary to technology, thus reducing the cost of adopting other, non-Medicare technologies. Perhaps more plausibly, PPS may also induce a switch in managerial effort from Medicare-related activities that have now become less profitable to non-Medicare activities, potentially inducing the adoption of non-Medicare technologies. Of course, a more prosaic explanation for the apparent "spillover" may be that, in practice, Medicare's cost-based reimbursement rules permitted hospitals considerable latitude in determining which costs to assign to Medicare (OTA 1984; CBO 1988), allowing some degree of fungibility in the reimbursement of capital expenses.

C. Changes in Skill Composition

Finally, result 3 suggests that when technology (or capital) is more complementary to skilled than to unskilled labor, the induced increase in technology (or in the capital-labor ratio) should cause a change in the composition of the workforce toward more skilled employees. We can identify full-time-equivalent employment of two types of nurses in the data, registered nurses (RNs) and licensed practical nurses (LPNs); together these constitute about one-quarter of total hospital employment.[26] RNs are considerably more skilled than LPNs.[27]

Column 5 of table 3 shows that the introduction of PPS appears to be associated with an increase in the proportion of nurses that are relatively more skilled (the RNs). These results are somewhat weaker than our previous findings because there is evidence of preexisting trends prior to PPS in the same direction as PPS and of magnitude about half of that estimated for PPS. Overall, we interpret the finding as broadly suggestive of a potential increase in the skill content of employment associated with the induced increase in technology adoption. Since, as discussed in the introduction, the existing view in the literature is that capital and technology are more complementary to skilled labor than to unskilled labor, evidence that PPS is associated with increases in the skill composition of hospitals' workforces provides indirect support for our results concerning the effect of PPS on capital-labor ratios and technology adoption.

[26] The total amount of hospital employment accounted by nurses is about one-third, but the other nursing categories do not have consistent names across years, making it impossible for us to use them in this exercise.

[27] RN certification requires about twice as many years of training as LPN certification, which is reflected in the approximately 50 percent higher hourly wage of RNs relative to LPNs. We are grateful to Doug Staiger for providing us with the estimates of hourly wages by occupation from the 2000 Merged Outgoing Rotation Groups of the Current Population Survey.

D. *Alternative Interpretations*

We have so far offered our preferred interpretation that the observed changes in factor demands and technology are a response to the change in relative factor prices induced by PPS. There are a number of alternative interpretations for the results reported so far. But the evidence suggests that these are less plausible than our preferred interpretation.

One potential alternative is that the increase in the depreciation share, documented in table 2, may be a mechanical effect. Depreciation is a backward-looking measure, and thus the ratio of depreciation to operating expenses may mechanically increase in response to a proportional scaling back of capital and labor inputs. But in practice, we see no scaling back of capital inputs, and moreover, this alternative explanation would suggest that the effect should attenuate over time, whereas the results in column 3 of table 2 indicate that the effect appears to grow over time. Another related concern would be that the PPS-induced reduction in hospitals' Medicare share (see col. 3 of table 3) could mechanically cause an increase in the capital-labor ratio if Medicare patients are treated in a less capital-intensive manner than non-Medicare patients. Empirically, however, Medicare patients appear to be more capital intensive than non-Medicare patients: in the 1983 cross section, hospitals with a higher Medicare share have a statistically significantly higher depreciation share, with or without controlling for a rich set of covariates. In addition, neither of these two "mechanical" explanations is consistent with the evidence of PPS-induced changes in technology adoption and skill composition.

Another possible interpretation is that the increase in the capital-labor ratio may partly reflect a strategic response by hospitals to the possibility that capital reimbursement may be made prospective in the future; if so, hospitals may wish to build up their historical capital costs to increase their future prospective capital reimbursement rates. The incentive for such a strategic response is not obvious, however, since it was not a priori clear if and when capital reimbursement would be made prospective, nor how or whether a hospital's own historical costs would affect any prospective reimbursement rates (see, e.g., GAO 1986; CBO 1988). Moreover, to the extent that the response reflects the results from such "gaming," we might expect it to occur predominantly—or at least disproportionately—on the more easily manipulatable financing dimension (e.g., interest expenditures or leveraging) rather than on the depreciation share per se. However, we found no evidence that PPS is associated with an increase in debt financing of capital expenditures ("leveraging up").[28] Finally, this type of gaming response should also

[28] These results are reported in Acemoglu and Finkelstein (2006).

not translate into effects on other margins, such as technology adoption or the skill composition of the workforce.[29]

One potential concern with the technology adoption results is the presence of secular increases in medical technology during this time period. Since the elderly are among the most intensive users of medical technology, there may be a spurious association between Medicare share and technology adoption trends. However, several of the technologies for which we find an impact of PPS are in fact not diffusing over our sample period (see fig. 5). Most important, the results from our prespecification test ($d_{1983} \cdot m_i$) in tables 4 and 5 show no systematic evidence of differential trends in technology adoption across hospitals with different Medicare shares before the introduction of PPS.

An alternative interpretation for our technology findings is that PPS reimbursement for Medicare patients (i.e., the price subsidy) is not fully prospective (McClellan 1996, 1997); the reimbursement a hospital receives for a Medicare patient varies on the basis not only of the patient's diagnosis, but also, in some cases, of the type of treatment he or she receives, particularly the type of surgery, if any. These features may have increased hospitals' incentives to perform these surgeries and consequently induced them to adopt the technologies needed to perform them. However, the evidence suggests that this type of incentive effect is unlikely to be the driving factor behind our technology adoption results since we find equally strong results for procedures that are not reimbursed more generously after PPS. As noted by McClellan (1996), for ad hoc reasons, there are separate reimbursement rates for patients who have a heart attack if they undergo percutaneous transluminal coronary angioplasty or coronary artery bypass graft, but not if they spend time in the cardiac care unit (CCU). Hazard models estimated for adoption of the CCU show that the introduction of PPS is associated with an increased rate of adoption of the CCU even though this was not a technology whose use was associated with any increased reimbursement rate.[30] Moreover, there is no evidence that hospitals vary resources per patient in response to the subsequent changes in Medicare's relative reimbursement rates of various health services (though

[29] Even if the effect is not merely a strategic one, the magnitude of the input response may be affected by hospitals' expectations that continued reimbursement of capital costs might be temporary. A priori, however, it is not clear how such expectations (even if they were important) would affect magnitudes. On the one hand, the response might be larger because the relative subsidy to capital is expected to be temporary and hospitals may attempt to incur and pass through their capital costs while they still can. On the other hand, if there are adjustment costs, the response may be smaller than the case in which the change in the regulatory regime is expected to be permanent.

[30] Information on whether a hospital has a CCU is available from 1980–85 (see App. table A1). The other technology adoption results in table 5 are robust to excluding 1986 from the data.

there is evidence of nominal responses, so-called up-coding; see, e.g., Dafny 2005).

Finally, since PPS applied only to hospital inpatient expenditures, it may have encouraged a real or nominal reallocation of some inpatient hospital activity to outpatient or nursing home units of the hospital. Previous empirical evidence suggests that PPS was, in fact, associated with reallocation of some inpatient hospital activity to hospital outpatient units, although there is no evidence of reallocation to nursing homes (Coulam and Gaumer 1991). However, any such reallocations within the hospital cannot explain our findings regarding the impact of PPS on input and technology choices since our input and technology measures are inclusive of hospital-based outpatient units and hospital-based nursing home facilities.[31] Of course, if some activities were spun off out of the hospital completely, these might potentially contribute to our estimated decline in labor inputs. Nevertheless, they cannot explain the estimated increase in technology adoption. Moreover, the empirical evidence is not suggestive of such spinoff behavior. We find no evidence that the introduction of PPS is associated with an increased probability of having a hospital-based nursing home unit (results not reported), and although we cannot use our empirical strategy to investigate the impact of PPS on the creation of freestanding nursing home facilities, there is no evidence in the time series of an increase in total nursing home use over our time period (HCFA 1999, 178).

VII. Robustness Checks

Table 6 reports the results for some of the robustness checks we performed on the depreciation share (capital-labor ratio) and the number of facilities (one of the measures of technology adoption).[32] Column 1 reproduces the baseline results from estimating equation (3). To investigate the concern that our results may be spuriously picking up underlying differential trends by hospitals with different pre-PPS Medicare shares, our first robustness exercise adds an interaction between the Medicare share (in 1983), m_i, and a linear trend (i.e., in terms of our estimating equations above, the vector of covariates $\mathbf{X}_{it}$ now includes $m_i \cdot t$). The estimates in column 2 show that our main results are robust to the inclusion of this linear trend.

A related but different concern is that of mean reversion. In particular, if high–Medicare share hospitals are adjusting back to some hospital-

[31] The estimated impact of PPS on the capital-labor ratio looks quite similar if we instead use measures of capital and labor that exclude any inputs used in a hospital-based nursing home (results not reported).

[32] Additional robustness analyses are presented and discussed in Acemoglu and Finkelstein (2006).

TABLE 6

Robustness Analysis: Alternative Specifications

	Base Case (1)	Add Linear Trend $\times m_i$ (2)	Add Year Dummies $\times$ Dependent Variable in 1982 (3)	First Differences (4)	Instrument for m_i with Past Values (5)	Using Only Within Variation (6)	Using Only Between Variation (7)
	A. Dependent Variable: Capital Labor Ratio (Depreciation Share)						
POSTTREND $\times m_i$	.532	.633	.657	.532	.511	.176	.787
	(.053)	(.114)	(.097)	(.059)	(.052)	(.092)	(.057)
$d_{1983} \times m_i$	−.060	.040	−.068	.064	−.131	.041	−.129
	(.088)	(.110)	(.182)	(.079)	(.087)	(.146)	(.101)
Observations	43,188	43,188	43,041	36,900	42,428	43,188	43,188
	B. Dependent Variable: Number of Facilities						
POST $\times m_i$	2.501	4.254	2.267	2.478	3.010	2.418	2.561
	(.401)	(.731)	(.377)	(.427)	(.383)	(.632)	(.494)
$d_{1983} \times m_i$	−.467	.410	−.566	.688	−.204	.135	−.896
	(.354)	(.459)	(.347)	(.333)	(.353)	(.553)	(.473)
Observations	43,188	43,188	43,041	36,900	42,428	43,188	43,188

Note.—The table reports results from estimating eqq. (3) and (5) by OLS. All regressions include hospital and year fixed effects. The dependent variable is given in the panel heading. The variable POST is an indicator variable for the years 1984–86. The variable POSTTREND = 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986, respectively. The variable d_{1983} is an indicator variable for the year 1983. The variable m_i measures the Medicare share of the hospital's inpatient days in 1983. The base case includes year and hospital fixed effects. Column 2 adds a linear time trend interacted with Medicare share in 1983 to the base case. Column 3 adds year dummies interacted with log total expenditures in 1982 to the base case. Column 4 redoes the base case in first differences instead of fixed effects. Column 5 instruments for Medicare share in 1983 with past values of the hospital's Medicare share (specifically, the values in 1980, 1981, and 1982). Column 6 adds a full set of year dummies interacted with each of the three categorical variables that can make a hospital exempt from PPS (federal ownership, long-term stays, or specialty hospital) so that the identification of the variables of interest comes only from within–hospital type variation in Medicare share. Column 7 instruments for POSTTREND $\times m_i$ and $d_{1983} \times m_i$ with a full set of year dummies interacted with the three categorical variables that can make a hospital exempt from PPS, so that the identification of the variables of interest comes only from between–hospital type variation in Medicare share. Standard errors are in parentheses and are adjusted to allow for an arbitrary covariance matrix within each hospital over time.

specific equilibrium level, this may be picked up by our post-PPS × Medicare share interaction. To investigate this issue, column 3 interacts the value of the dependent variable for each hospital in 1982 with a full set of year dummies. This specification thus flexibly controls for any mean-reverting dynamics as well as any potential differential trends that depend on hospital baseline characteristics (e.g., based on technology levels). The estimates are remarkably similar to the baseline and show no evidence that mean reversion or differential trends based on pretreatment characteristics had any significant effect on our results.

As another check on the serial correlation properties of the error term and patterns of mean reversion, column 4 estimates the model in first differences rather than in levels. This specification is also useful as a check on the strict exogeneity assumption necessary for consistency of the fixed-effects estimator (Wooldridge 2002, 284) and on the potential importance of measurement error in the data (Griliches and Hausman 1986). For the depreciation share, the first-differenced results in column 4 are very similar to the baseline results. However, for the number of facilities, the results now show a pre-PPS effect of the same sign as the estimated PPS effect that is significant at 5 percent. However, since this is the only specification among many in which we find a same-signed significant pre-PPS effect for the number of facilities, we interpret this as partly driven by sampling variability.

Column 5 deals with concerns about measurement error in our key variable, the Medicare share, by instrumenting for the 1983 Medicare share with past values. The results are again similar to the baseline estimates.

We explored the heterogeneity in the estimated effect of PPS based on the type of variation in m_i used to identify its effects. Recall that federally owned hospitals, long-term hospitals, and certain specialty hospitals—together totaling 15 percent of all hospitals—were exempted from PPS and were coded as having a zero Medicare share (see fig. 4). We explored how the estimated effect of PPS varies depending on whether we use the variation in Medicare share provided by these exempt hospitals to identify the effect of PPS. In column 6, we add a full set of year dummies interacted with each of the three categories that provide an exemption from PPS to equations (3) and (5). As a result, identification of the effect of PPS comes only from within–hospital type variation in m_i, and the three types of hospitals that are exempt from Medicare PPS are not used to estimate its impact. Column 7 presents the complementary approach in which identification of PPS comes only from between–hospital type variation in m_i. Here, we instrument the interaction terms $d_{1983} \cdot m_i$ and $\mathrm{POSTTREND}_t \cdot m_i$ or $\mathrm{POSTTREND}_t \cdot m_i$ with the full set of year dummies interacted with each of the three exemption categories. The results indicate that the basic findings are robust to using either the within or between variation, although the estimated impact of PPS on the capital-labor ratio is substantially larger using the between variation than the within variation.

We also briefly explored potential heterogeneity in the impact of PPS across hospitals of different ownership types and across hospitals facing different degrees of competition (again results not shown here). The estimated impact of PPS appears to be quite similar across publicly owned, for-profit, and nonprofit hospitals. It is also quite similar across hospitals that are monopoly providers in their county compared to hospitals that face one or more competitor hospitals in their county. The one exception is that the technology adoption effects of PPS appear to be more pronounced in publicly owned hospitals (results not shown).

Finally, we considered the sensitivity of our results to allowing for differential trends in different parts of the country. In particular, since the price subsidy of Medicare PPS was phased in over a 4-year period as a combination of hospital-specific historical rates, regional average rates, and national rates (CBO 1988; Staiger and Gaumer 1990), regional differences in the level of the price subsidy might contribute to differential regional effects of PPS. We therefore verified that the results are not affected by including a full set of interactions between the (nine) census region dummies and year effects (not shown). Another potential source of confounding time-varying geographic factors is that seven states—constituting about one-fifth of the hospitals in our sample—experienced some change in their Certificate of Need (CON) laws during our time period. We verified that our results are robust in both statistical significance and magnitude to excluding these seven states (not shown).[33]

VIII. Conclusions

This paper has investigated the impact of regulatory change on firm input mix and technology choices, focusing on the introduction of the Medicare Prospective Payment System in the United States. This reform changed the reimbursement for Medicare-related inpatient hospital expenses from a full cost reimbursement system for both labor and capital inputs to a partial cost reimbursement system and thereby raised the relative price of labor.

We argued that the introduction of PPS increased the price of labor faced by hospitals, in particular, for hospitals with a high share of Medicare patients, while leaving the price of capital unchanged. A simple

[33] More details on the CON reforms can be found at http://www.ncsl.org/programs/health/cert-need.htm.

neoclassical framework indicates that this change in relative prices should lead to an increase in the capital-labor ratio. More interestingly, our framework shows that PPS could also increase the overall demand for capital and induce technology adoption.

Consistent with these implications, our empirical results suggest that the PPS reform is associated with an increase in the capital-labor ratio. This decline stems mainly from a decline in labor inputs. We also found that the introduction of PPS is associated with a significant increase in the adoption of a range of new health care technologies. This increase in technology adoption would be predicted when there is a relatively high degree of substitutability between technology and hospital labor. We presented suggestive evidence of technology-labor substitution working through declines in the length of stay. We also found an increase in the skill composition of these hospitals, which is consistent with technology-skill (or capital-skill) complementarities.

Our empirical findings suggest that relative factor prices are an important determinant of technology diffusion in the hospital sector and perhaps in other sectors as well. They raise an interesting question for further research of whether other factors that increase the relative price of labor for hospitals, such as labor unions or the tax treatment of capital expenditures, also encourage capital deepening and technology adoption.

Our findings do not address the efficiency and welfare consequences of the increase in relative labor prices associated with a move to PPS. These depend in part on the relative generosity of labor and capital reimbursement under the previous full cost reimbursement system and also on other preexisting distortions in the health care sector. However, the evidence that the move to PPS was not associated with substantial adverse health outcomes (Staiger and Gaumer 1990; Cutler 1995) suggests that at least on the health dimension there were no substantial adverse welfare effects.

It is also worth emphasizing that our findings regarding technology adoption run counter to the general expectation that PPS would likely reduce the pace of technology adoption (Sloan et al. 1988; Coulam and Gaumer 1991; Weisbrod 1991). Such expectations were formed by considering PPS as a full price cap system and hence overlooked the associated relative factor price changes. This highlights the potential importance of the details of regulation policy in determining its ultimate impact. The particular detail we have focused on—the exemption of capital costs from prospective reimbursement systems—appears to be quite common in practice. For example, the subsequent Medicare prospective payment reimbursement system for home health care also excluded capital-related costs (in particular, “durable medical equipment” such as hospital beds or oxygen equipment) from the price cap (*Federal Register*, July 3, 2000).

Naturally, our empirical results directly speak only to the impact of regulatory change in the hospital sector. It is possible that the health care sector is not representative of regulatory effects in other sectors, for example, because most hospitals are nonprofit or public entities or because the health care sector is significantly less capital intensive than many other regulated industries (recall n. 13). Nevertheless, the ideas presented here should also apply to other regulated industries, many of which operate under some form of partial cost reimbursement (see Joskow 2005). In light of this, we may expect that a switch to partial cost reimbursement in other regulated industries may have also increased capital-labor ratios and perhaps even encouraged technology adoption, though we are not aware of any direct evidence on this. An investigation of the response of input and technology choices to similar regulatory changes in other industries is another interesting area for future research and would be particularly useful for understanding the extent to which the results presented here generalize to other industries.

Appendix A

TABLE A1
DESCRIPTION OF 113 BINARY FACILITIES IN THE DATA FOR 1980–86

Facility Description	Years in Data	Sample Mean
Abortion services (inpatient or outpatient)	1980–85	.22
Adult day care	1986	.05
AIDS services	1986	.28
Alcoholism/chemical dependency acute and subacute inpatient care	1980–85	.26
Alcoholism/chemical dependency services (outpatient)	1981–86	.17
Ambulance services	1980–81	.17
Ambulatory surgical services	1981–86	.80
Anesthesia service	1980–81	.72
Autopsy services	1980–81	.47
Birthing room	1985–86	.44
Blood bank	1980–86	.64
Burn care	1980–85	.09
Cancer tumor registry	1980–81	.30
Cardiac catheterization	1980–86	.16
Cardiac intensive care	1980–85	.67
Chaplaincy services	1980–85	.55
Clinical psychology services	1980–86	.33
Community health promotion	1986	.54
Continuing care case management	1986	.15
Contraceptive care	1986	.09
CT scanner (head or body unit)	1980–86	.34
Day hospital	1981–86	.17
Dental services	1980–85	.48
Diagnostic radioisotope facility	1980–86	.56
Diagnostic x-ray	1985–86	.89
Electrocardiography	1980–85	.91
Electroencephalography	1980–81	.50
Electromyography	1980–81	.27
Emergency department	1981–86	.85
Extracorporeal shock wave lithotripter	1985–86	.02
Family planning	1980–85	.10
Fertility counseling	1986	.09
Fitness center	1986	.09
General laboratory services	1980–81, 1984–85	.88
General surgical services	1980–81, 1983–85	.87
Genetic counseling	1980–86	.06
Genetic screening	1986	.06
Geriatric acute-care unit	1986	.12
Geriatric assessment services, comprehensive	1982–86	.13
Geriatric clinics, satellite	1986	.02
Health promotion	1981–85	.40
Hemodialysis (home care/mobile unit)	1980–81	.04
Hemodialysis services (inpatient or outpatient)	1980–86	.21
Histopathology services	1980–86	.56
Home care program	1980–86	.18
Hospice	1980–86	.08
Hospital auxiliary	1980–86	.75

TABLE A1
(*Continued*)

Facility Description	Years in Data	Sample Mean
Intermediate care for mentally retarded	1980–85	.03
Intermediate care, other	1980–85	.13
Intravenous admixture services	1980–85	.71
Intravenous therapy team	1980	.25
Medical library	1980–81	.84
Medical/surgical acute care	1980–85	.91
Medical/surgical intensive care	1980–85	.74
Megavoltage radiation therapy	1980–86	.14
Neonatal intensive care	1980–85	.09
Neurosurgery	1980–81	.29
Newborn nursery	1980–85	.70
Nuclear magnetic resonance facility	1983–86	.04
Obstetrical care	1980–85	.70
Occupational health services	1986	.23
Occupational therapy	1980–86	.40
Open-heart surgery	1980–86	.11
Optometric services	1981–85	.16
Organ bank	1980–81	.03
Organ transplant (including kidney)	1980–86	.05
Organized outpatient department	1981–86	.49
Patient education	1986	.67
Patient representative services	1980–86	.49
Pediatric acute care	1980–85	.75
Pediatric intensive care	1980–85	.18
Percutaneous lithotripsy	1985	.11
Pharmacy service (full- or part-time)	1980–85	.91
Pharmacy unit dose system	1980–85	.71
Physical therapy	1980–86	.79
Podiatric services (inpatient or outpatient)	1980–85	.31
Postoperative recovery room	1980–82	.83
Premature nursery	1980–85	.26
Psychiatric acute care	1980–85	.36
Psychiatric consultation and education	1980–86	.29
Psychiatric emergency services	1981–86	.32
Psychiatric foster and/or home care program	1980–86	.03
Psychiatric intensive care	1980–82	.13
Psychiatric liasion services	1983–86	.16
Psychiatric long-term care	1980–85	.06
Psychiatric outpatient services	1981–86	.18
Psychiatric partial hospitalization program	1980–86	.13
Psychiatric services, pediatric	1981–86	.14
Pulmonary function laboratory	1980–81	.58
Radioactive implants	1980–86	.20
Recreational therapy	1980–86	.30
Rehabilitation	1980–85	.30
Rehabilitation services (outpatient)	1981–86	.32
Residential care	1980	.05
Respiratory therapy	1980–86	.81
Respite care	1986	.09
Self care	1980–85	.06
Sheltered care	1981–85	.02
Skilled nursing, long-term	1980–85	.16

TABLE A1
(*Continued*)

Facility Description	Years in Data	Sample Mean
Social work services	1980–85	.77
Speech therapy	1980–86	.36
Special care, other	1981–85	.22
Sports medicine clinic/service	1986	.11
Sterilization	1986	.23
Therapeutic radioisotope facility	1980–86	.21
Toxicology/antidote information	1980–81	.38
Trauma center	1984–86	.17
Tuberculosis and other respiratory diseases	1980–86	.34
Ultrasound	1981–86	.69
Volunteer services	1980–86	.65
Women's center	1986	.09
Work site health promotion	1986	.35
X-ray radiation therapy	1980–86	.16

NOTE.—All facilities are coded directly from a single variable in the data except for neonatal intensive care unit, where we followed the coding procedure of Baker and Phibbs (2002), and the following seven variables, which we generated as a consistent series using combinations of different variables in different years: (1) Abortion services (inpatient or outpatient): coded 1 in 1980 and 1981 if the hospital reports having either inpatient abortion services or outpatient abortion services or both; coded 1 in 1982–85 if the hospital reports having abortion services. (2) Alcoholism/chemical dependency acute and subacute inpatient care: coded 1 in 1984 if the hospital reports having alcohol/chemical dependency acute inpatient care or alcohol/chemical dependency subacute inpatient care or both; coded 1 in 1980–83, 1985 if hospital reports having alcohol/chemical dependency inpatient care. (3) CT scanner (head or body unit): coded 1 in 1980 and 1981 if the hospital reports having either a CT scanner head unit or a CT scanner body unit or both; coded 1 in 1982–86 if the hospital reports having a CT scanner. (4) Pharmacy service (full- or part-time): coded 1 in 1980 or 1981 if the hospital reports having either a full-time or a part-time pharmacist or both; coded 1 in 1982–85 if the hospital reports having pharmacy services. (5) Hemodialysis services (inpatient or outpatient): coded 1 in 1980 and 1981 if the hospital reports having either hemodialysis inpatient services or hemodialysis outpatient services or both; coded 1 in 1982–86 if hospital reports having hemodialysis services. (6) Organ transplant (including kidney): coded 1 in 1980–85 if the hospital reports having either organ transplant capability (other than kidney) or kidney transplant capability or both; coded 1 in 1986 if hospital reports having organ transplant capability (including kidney). (7) Podiatric services (inpatient or outpatient): coded 1 in 1981 if the hospital reports having inpatient or outpatient podiatric services or both; coded 1 in 1980, 1982–85 if hospital reports having podiatric services.

References

Acemoglu, Daron. 2002. "Technical Change, Inequality and the Labor Market." *J. Econ. Literature* 40 (1): 7–72.

Acemoglu, Daron, and Amy Finkelstein. 2006. "Input and Technology Choices in Regulated Industries: Evidence from the Health Care Sector." Working Paper no. 12254 (May), NBER, Cambridge, MA.

Acemoglu, Daron, and Joshua Linn. 2004. "Market Size in Innovation: Theory and Evidence from the Pharmaceutical Industry." *Q.J.E.* 119 (3): 1049–90.

AHA (American Hospital Association). 1983. *Estimated Useful Lives of Depreciable Hospital Assets*. Chicago: American Hospital Assoc.

Antos, Joseph. 1993. "Waivers, Research, and Health System Reform." *Health Affairs* 12 (1): 179–83.

Armstrong, Mark, Simon Cowen, and John Vickers. 1994. *Regulatory Reform: Economic Analysis and British Experience*. Cambridge, MA: MIT Press.

Autor, David, Lawrence F. Katz, and Alan B. Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *Q.J.E.* 113 (November): 1169–1214.

Averch, Harvey, and Leland Johnson. 1962. "Behavior of the Firm under Regulatory Constraint." *A.E.R.* 52 (5): 1053–69.

Baicker, Katherine, and Douglas Staiger. 2005. "Fiscal Shenanigans, Targeted Federal Health Care Funds, and Patient Mortality." *Q.J.E.* 120 (1): 345–86.

Baker, Laurence. 1997. "The Effect of HMOs and Fee-for-Service Health Care Expenditures: Evidence from Medicare." *J. Health Econ.* 16 (4): 453–81.

———. 2001. "Managed Care and Technology Adoption in Health Care: Evidence from Magnetic Resonance Imaging." *J. Health Econ.* 20 (3): 395–421.

Baker, Laurence, and Ciaran Phibbs. 2002. "Managed Care, Technology Adoption, and Health Care: The Adoption of Neonatal Intensive Care." *Rand J. Econ.* 33 (3): 524–48.

Baumol, William, and Alvin Klevorick. 1970. "Input Choices and Rate-of-Return Regulation: An Overview of the Discussion." *Bell J. Econ. and Management Sci.* 1 (1): 162–90.

Berman, Eli, John Bound, and Zvi Griliches. 1994. "Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufacturers." *Q.J.E.* 109 (May): 367–97.

Cawley, John, David Grabowski, and Richard Hirth. 2006. "Factor Substitution in Nursing Homes." *J. Health Econ.* 25 (2): 234–47.

CBO (Congressional Budget Office). 1988. "Including Capital Expenses in the Prospective Payment System." Report, Congressional Budget Off., Washington, DC.

Cotterill, Philip. 1991. "Prospective Payment for Medicare Hospital Capital: Implications of the Research." *Health Care Financing Rev.* (suppl.): 79–86.

Coulam, Robert, and Gary Gaumer. 1991. "Medicare's Prospective Payment System: A Critical Appraisal." *Health Care Financing Rev.* (suppl.): 45–77.

Cutler, David. 1995. "The Incidence of Adverse Medical Outcomes under Prospective Payment." *Econometrica* 63 (1): 29–50.

———. 2003. *Your Money or Your Life: Strong Medicine for America's Health Care System.* New York: Oxford Univ. Press.

Cutler, David, and Louise Sheiner. 1998. "Managed Care and the Growth of Medical Expenditures." In *Frontiers in Health Policy Research*, edited by Alan Garber. Cambridge, MA: MIT Press.

Cutler, David, and Richard Zeckhauser. 2000. "The Anatomy of Health Insurance." In *Handbook of Health Economics*, vol. 1A, edited by Anthony Culyer and Joseph Newhouse. Amsterdam: Elsevier.

Dafny, Leemore. 2005. "How Do Hospitals Respond to Price Changes?" *A.E.R.* 95 (5): 1525–47.

Feder, Judith, Jack Hadley, and Stephen Zuckerman. 1987. "How Did Medicare's Prospective Payment System Affect Hospitals?" *New England J. Medicine* 317 (14): 867–73.

Finkelstein, Amy. 2004. "Static and Dynamic Effects of Health Policy: Evidence from the Vaccine Industry." *Q.J.E.* 119 (2): 527–64.

———. 2007. "The Aggregate Effects of Health Insurance: Evidence from the Introduction of Medicare." *Q.J.E.* 122 (1): 1–37.

Fuchs, Victor. 1996. "Economics, Values, and Health Care Reform" (presidential address of the American Economic Association). *A.E.R.* 86 (1): 1–24.

GAO (General Accounting Office). 1986. "Medicare: Alternative for Paying Hospital Capital Costs." Report, Gen. Accounting Off., Washington, DC.

Greenstone, Michael. 2002. "The Impacts of Environmental Regulation on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures." *J.P.E.* 110 (6): 1175–1219.

Griliches, Zvi. 1956. "Capital-Skill Complementarity." *Rev. Econ. and Statis.* 51 (3): 465–68.

Griliches, Zvi, and Jerry Hausman. 1986. "Errors in Variables in Panel Data." *J. Econometrics* 31 (1): 93–118.

Habakkuk, H. J. 1962. *American and British Technology in the Nineteenth Century: Search for Labor Saving Inventions.* New York: Cambridge Univ. Press.

Hausman, Jerry, Bronwyn Hall, and Zvi Griliches. 1984. "Econometric Models for Count Data with an Application to the Patents-R&D Relationship." *Econometrica* 52 (4): 909–38.

HCFA (Health Care Financing Administration). 1986. *Status Report: Research and Demonstrations in Health Care Financing.* Baltimore: U.S. Dept. Health and Human Services.

———. 1987. *Status Report: Research and Demonstrations in Health Care Financing.* Baltimore: U.S. Dept. Health and Human Services.

———. 1999. *Statistical Supplement.* Baltimore: U.S. Dept. Health and Human Services.

Hicks, John. 1932. *The Theory of Wages.* London: Macmillan.

Joskow, Paul. 2005. "Incentive Regulation in Theory and Practice: Electricity Distribution and Transmission Networks." Manuscript, Dept. Econ., Massachusetts Inst. Tech.

Kiefer, Nicholas. 1988. "Economic Duration Data and Hazard Functions." *J. Econ. Literature* 26 (2): 646–79.

Kling, Jeffrey, and Jeffrey Liebman. 2004. "Experimental Analysis of Neighborhood Effects on Youth." Manuscript, Dept. Econ., Princeton Univ.

Krusell, Per, Lee Ohanian, Victor Rios-Rull, and Giovanni Violante. 2000. "Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis." *Econometrica* 68 (5): 1029–53.

Laffont, Jean-Jacques, and Jean Tirole. 1993. *A Theory of Incentives in Procurement and Regulation.* Cambridge, MA: MIT Press.

McClellan, Mark. 1996. "Medicare Reimbursement and Hospital Cost Growth." In *Advances in the Economics of Aging*, edited by David Wise. Chicago: Univ. Chicago Press.

———. 1997. "Hospital Reimbursement Incentives: An Empirical Analysis." *J. Econ. and Management Strategy* 6 (1): 91–128.

MedPAC (Medicare Payment Advisory Commission). 1999. "Report to Congress: Medicare Payment Policy." http://www.medpac.gov.

Newell, Richard, Adam Jaffe, and Robert Stavins. 1999. "The Induced Innovation Hypothesis and Energy-Saving Technological Change." *Q.J.E.* 114 (3): 941–75.

Newhouse, Joseph. 1992. "Medicare Care Costs: How Much Welfare Loss?" *J. Econ. Perspectives* 6 (3): 3–21.

———. 2002. *Pricing the Priceless: A Health Care Conundrum.* Cambridge, MA: MIT Press.

OTA (Office of Technology Assessment). 1984. "Medical Technology and the Costs of the Medicare Program." Report, Government Printing Off., Washington, DC.

———. 1985. "Medicare's Prospective Payment System: Strategies for Evaluating Cost, Quality, and Medical Technology." Report, Government Printing Off., Washington, DC.

PPAC (Prospective Payment Assessment Commission). 1988. "Medicare Prospective Payment and the American Health Care System: Report to the Congress." Report, Prospective Payment Assessment Comm., Washington, DC.

———. 1990. "Medicare Prospective Payment and the American Health Care System: Report to the Congress." Report, Prospective Payment Assessment Comm., Washington, DC.

———. 1992. "Medicare Prospective Payment and the American Health Care System: Report to the Congress." Report, Prospective Payment Assessment Comm., Washington, DC.

Sloan, Frank. 2000. "Not-for-Profit Ownership and Hospital Behavior." In *Handbook of Health Economics*, vol. 1B, edited by Anthony Culyer and Joseph Newhouse. Amsterdam: Elsevier.

Sloan, Frank, Michael Morrissey, and Joseph Valvona. 1988. "Medicare Prospective Payment and the Use of Medical Technologies in Hospitals." *Medical Care* 26 (9): 837–53.

Staiger, Douglas, and Gary Gaumer. 1990. "The Impact of Financial Pressure on Quality of Care in Hospitals: Post-admission Mortality under Medicare's Prospective Payment System." Report, Abt Assoc., Cambridge, MA.

Staiger, Douglas, Joanne Spetz, and Ciaran Phibbs. 1999. "Is There Monopsony in the Labor Market? Evidence from a Natural Experiment." Working Paper no. 7258 (July), NBER, Cambridge, MA.

Weisbrod. Burton. 1991. "The Health Care Quadrilemma: An Essay on Technological Change, Insurance, Quality of Care, and Cost Containment." *J. Econ. Literature* 29 (2): 523–52.

Westfall, Peter H., and Stanley S. Young. 1993. *Resampling-Based Multiple Testing: Examples and Methods for P-Value Adjustment.* New York: Wiley.

Wooldridge, Jeffrey. 2002. *Econometric Analysis of Cross Section and Panel Data.* Cambridge, MA: MIT Press.

Yin, Wesley. 2005. "Do Market Incentives Generate Innovation or Balkanization? Evidence from the Market for Rare Disease Drugs." Manuscript, Dept. Econ., Univ. Chicago.