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

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Abstract

This paper examines the implications of regulatory change for the input mix and technology choices of regulated industries. We present a simple neoclassical framework that emphasizes changes in relative factor prices faced by regulated firms under different regimes, and investigate how this might affect their technology choices through substitution of (capital embodied) technologies for tasks previously performed by labor. We examine some of the implications of the framework empirically by studying the change from full cost to partial cost reimbursement under the Medicare Prospective Payment System (PPS) reform, which increased the relative price of labor faced by U.S. hospitals. Using the interaction of hospitals' pre-PPS Medicare share of patient days with the introduction of these regulatory changes, we document a substantial increase in capital-labor ratios and a large decline in labor inputs associated with PPS. Most interestingly, we find that the PPS reform seems to have encouraged the adoption of a range of new medical technologies. We also show that the reform was associated with an increase in the skill composition of these hospitals, which is consistent with technology-skill or capital-skill complementarities.

Keywords: health care, hospitals, labor demand, Medicare, Prospective Payment System, regulation, technology.

JEL Classification: H51, I18, L50, L51, O31, O33

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1 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 as health care, electricity and telecommunications, which are not only 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 regulation regime.

Starting in the mid-1980s, a number of different industries in a variety of countries experienced a change in regulation regime away from full cost reimbursement towards some type of "price cap".[1] These new regulation 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, while labor expenses are supposed to be covered by the fixed price paid per unit of output. A change from full cost to partial cost reimbursement therefore 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, p. 36) notes:

> "Although it is not discussed too much in the empirical literature, the development of the parameters of price cap mechanisms.... have typically focused primarily on operating costs only, with capital cost allowances established through more traditional utility planning and cost-of-service regulatory accounting methods".

To investigate the implications of changes in regulation away from full cost reimbursement, we develop a simple neoclassical model of firm behavior under regulation. The most common

[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, for example, Laffont and Tirole 1993, Armstrong, Cowen and Vickers, 1994, Joskow, 2005) and the Medicare Prospective Payment System for US hosptials which is the focus of this paper.

approaches to regulation are the optimal regulation models, for example as in Laffont and Tirole (1993), and the rate of return regulation of Averch and Johnson (1962). Neither is appropriate as a framework for guiding empirical work in this setting, however, for at least two reasons. First, cost reimbursement regulation, both in general and in the health care sector in particular, does not have the optimal screening structure posited in Laffont and Tirole-type optimal regulation models, nor does cost reimbursement in the health care sector regulate the rate of return on capital as in the Averch and Johnson model. Second, neither of these two approaches provides a framework for analyzing technology adoption decisions resulting from a change in regulation regime (although it may in principle be possible to consider such extensions of these approaches).

Our framework is similar to Averch and Johnson (1962), but focuses on cost reimbursement rather than rate of return regulation. It links the input and technology choices of firms to the relative factor prices they face, which are themselves determined by the regulation regime. We show that under fairly mild assumptions, a change in regulation regime from full cost to partial cost reimbursement will be associated with an increase in capital-labor ratios.

The implications of the change in regulation for the overall level of labor and capital inputs (and the scale of activity) are ambiguous, and depend on the generosity of the partial price cap replacing cost reimbursement. In the context of the Medicare PPS reform, existing qualitative and empirical evidence suggests a relatively low price cap, and we present evidence that the reform is associated with a decline in overall labor inputs and in the Medicare share of hospital activity, both of which would be predicted by our framework if the level of the price cap is sufficiently low. Despite the decline in labor inputs, our simple framework shows that capital expenditures can increase, and perhaps more surprisingly, the firm may be induced to adopt more advanced technologies. This configuration is more likely when there are decreasing returns to capital and labor (or technology and labor) jointly and the elasticity of substitution between these factors is high. Intuitively, the increased relative price of labor induces the firm to substitute technology and capital embodying new technologies for tasks previously performed by labor. This result has implications for the famous *labor push theory of innovation* suggested by Hicks (1932)and Habakkuk (1962), which claims that higher wages encourage innovation. Although such a configuration cannot happen in the basic neoclassical growth models with competitive markets and constant returns to capital and labor, we derive conditions under which such a result might obtain, and show that these conditions are not very restrictive.[2]

[2]Strictly speaking, the labor push theory of innovation refers to the case in which the only change is an

The bulk of the paper empirically investigates the impact of the Medicare Prospective Payment System (PPS) in the United States. PPS, introduced in October 1983, switched reimbursement for hospital inpatient expenses of Medicare patients from full cost reimbursement to partial cost reimbursement. The motivation behind this reform was to reduce the level and growth of hospital spending, which had been rising rapidly (as a share of GDP) for several decades.

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 sector 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). Second, government regulation is ubiquitous in this industry. Third, the PPS reform provides an opportunity to study the impact of a change in regulation regime from full cost reimbursement to partial cost reimbursement, with significant changes in relative factor prices faced by hospitals. 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.

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 share 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.[3] Interestingly, this pattern is not only detectable in our panel data approach, which analyzes differential trends by hospitals with different pre-PPS Medicare shares, but the effect of PPS seems to have been large enough to be also visible in the aggregate time series, where there is a notable increase in the average capital-intensity

increase in the price of labor. In the theory section, we derive the conditions under which such a change in the price of labor will encourage technology adoption (or capital deepening). However, 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 for health services provided to Medicare patients). Our empirical results on the effect of PPS on technology adoption therefore do not provide direct evidence for the labor push theory.

[3] Hospital labor consists of nurses, technicians and administrators. Most doctors are neither hired nor paid directly by hospitals.

of hospitals. This change in the capital-labor ratio is made up of a decline in the labor inputs of high-Medicare share hospitals, with approximately constant capital inputs. Again, the same pattern is present both in the panel data analysis and in the simple time series.

Perhaps most interestingly, we find that the introduction of PPS is also 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.[4] 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 has been 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, Krusell et al., 2000 Berman et al. 1994, Autor et al. 1998, Acemoglu, 2002).

Our finding that PPS is associated with an increase in technology adoption, as well as in capital-labor ratios, is consistent with the predictions of the motivating theory. We consider a number of alternative interpretations for the empirical patterns that we document below, and conclude that the balance of evidence does not favor any of these alternatives. We therefore interpret the post-PPS 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.[5]

[4] As we discuss below, increased technology adoption, combined with more or less constant overall capital expenidtures, suggests that there was likely a decline in some other type of capital expenditures, such as structures.

[5] In this respect, our paper is related to that of Newell et al. (1999) who look at the effect of environmental regulation, as well as as energy price increases, on the energy efficiency of a variety of appliances. See also Greenstone (2002) on the effect of environmental regulations in general 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, 2005) and to slow in response to managed care organizations (Cutler and Sheiner, 1998, Baker, 2001, Baker and Phibbs, 2002). There is also evidence that 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 investment (Yin, 2005).

It is also noteworthy that our finding runs counter to the general expectation that PPS would slow the growth of expensive technology diffusion (see, for example, Sloan et al., 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 non-capital 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.[6]

The rest of the paper proceeds as follows. In Section 2, we develop a simple neoclassical framework to investigate the implications of the change in regulation regime on input and technology choices. Section 3 reviews the relevant institutional background on Medicare reimbursement of inpatient hospital expenses. Section 4 describes the data and presents some descriptive statistics. The econometric framework is presented in Section 5. Our main empirical results are presented in Section 6, while Section 7 shows that they are robust to a number of alternative specifications. Section 8 concludes. Appendix A contains the proofs from Section 2, and Appendix B discusses a number of further theoretical issues.

2 Motivating Theory

There are many conceptual difficulties in modeling both the demand for and supply of health care, since the demand for health care is often determined by the technologies and the diagnoses that are available, and neither the supply nor the demand for health care can be separated from various private and social insurance policies and government regulation. Our purpose here is not to present a comprehensive model of the health care market, but rather to develop an organizing framework for the empirical work, and also to provide some simple insights that are applicable to other industries regulated by full cost or partial cost reimbursement.

2.1 A Neoclassical Model of Regulation

2.1.1 Environment

Four simplifying assumptions in our approach are worth highlighting at the outset.

The first is that hospitals, despite many being non-profit or public organizations, maximize profits. Clearly, non-profit or public organizations have other objectives as well, but starting with the profit-maximizing case is a useful benchmark. It is also consistent with a large empirical literature that finds essentially no evidence of differential behavior across for-profit

[6] The literature on PPS is revised in Section 3.

and non-profit hospitals (see Sloan, 2000 for a recent review of this literature). Second, we assume that, at least at the margin, there is considerable *fungibility* between labor and capital inputs used for Medicare purposes and labor and capital inputs used for non-Medicare purposes (OTA, 1984, CBO, 1988). This allows us to model Medicare input reimbursement as taking a simple form in which hospital i is reimbursed for a fraction m_i of its capital and labor costs, where m_i is the "Medicare share" of this hospital. Appendix B shows that the basic implications of our analysis of the impact of a change in regulation regime continue to hold when we no longer allow fungibility between Medicare and non-Medicare inputs. Third, we assume that the hospital is a price taker in the 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] Finally, we assume that hospitals are price takers for Medicare patients.[8]

Suppose that hospital i has a production function for total health services given by

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

where L_i and K_i are total labor and capital hired by this hospital, z_i is some other input, such as managerial effort (or perhaps, other medical inputs, such as doctors who are not directly hired and paid by hospitals themselves), and A_i is a productivity term, which may potentially differ across hospital, for example because of their technology choices or other reasons. We assume that $\tilde{F}$ is increasing in all of its inputs and twice continuously differentiable for positive levels of inputs.

For simplicity, we will interpret (1) as the production function of the hospital, though equivalently, it could be interpreted as its revenue function (with the price substituted in as a function of quantity). We also assume that z_i is fixed, and, without loss of any generality, we normalize it to $z_i = 1$, and begin with the case in which A_i is exogenous. This gives:

$$F(A_i, L_i, K_i) \equiv \tilde{F}(A_i, L_i, K_i, z_i = 1), \tag{2}$$

which we assume exhibits decreasing returns to scale in capital and labor (for example, because the original production function $\tilde{F}$ exhibited constant returns to scale). Since $\tilde{F}$ was

[7] In practice, some hospitals might have monopsony power for some component of their labor demand. For example, Staiger et al. (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.

[8] In practice, however, unlike in the standard model of perfectly competitive firms, 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 where the firm chooses both quantity and quality, and there is *quality competition.* Although we believe this is an important area for theoretical analysis, it falls outside the scope of our paper.

increasing in its inputs and twice continuously differentiable for positive inputs, so is F, and we denote the partial derivatives by F_L and F_K (and the second derivatives by F_{LL}, F_{KK} and F_{LK}). Moreover, we make the standard Inada type assumption that $\lim_{L_i \to 0} F_L(A_i, L_i, K_i) = \lim_{K_i \to 0} F_K(A_i, L_i, K_i) = \infty$ and $\lim_{L_i \to \infty} F_K(A_i, L_i, K_i) = \lim_{K_i \to \infty} F_K(A_i, L_i, K_i) = 0$. In addition, we will often look at the cases in which $F(A_i, L_i, K_i)$ is homothetic or homogeneous in L_i and K_i, or in A_i and L_i.[9]

2.1.2 Full Cost Reimbursement Regulation

Under the original regulation, which we refer to as *full cost reimbursement*, the hospital receives reimbursement for some fraction of its labor and capital used for Medicare purposes.[10] It also receives a copayment from Medicare patients as well as revenues from non-Medicare patients (where the hospital might have some market power, which we are incorporating into the F function). Denoting the total price per unit of health care services under the cost reimbursement regulation system by $q > 0$, the maximization problem of the hospital is

$$\max_{L_i, K_i} \pi^f(i) = qF(A_i, L_i, K_i) - (1 - m_i s_L) wL_i - (1 - m_i s_K) RK_i, \tag{3}$$

where $s_L < 1$ and $s_K < 1$ are constants capturing the relative generosity of labor and capital Medicare reimbursement and $m_i \in [0, 1]$ is the Medicare share of the hospital.[11] In subsection 2.2 we will endogenize m_i, but for now, we take it as given.

The first-order conditions of this maximization problem are

$$qF_L\left(A_i, L_i^f, K_i^f\right) = (1 - m_i s_L) w, \text{ and} \tag{4}$$

$$qF_K\left(A_i, L_i^f, K_i^f\right) = (1 - m_i s_K) R, \tag{5}$$

for labor and capital, respectively, where the superscript f refers to full cost reimbursement.

[9] If $F(A_i, L_i, K_i)$ is homothetic in L_i and K_i, then $F_K(A_i, L_i, K_i) / F_L(A_i, L_i, K_i)$ is only a function of K_i/L_i. Alternatively, homotheticity in L_i and K_i is equivalent to $F(A_i, L_i, K_i) \equiv H_1(A_i) H_2(\phi(L_i, K_i))$, where $H_1(\cdot)$ and $H_2(\cdot)$ are increasing functions, and ϕ is increasing in both of its arguments and exhibits constant returns to scale.

If $F(A_i, L_i, K_i)$ is homogeneous of degree α in L_i and K_i, then $F_K(A_i, L_i, K_i) / F_L(A_i, L_i, K_i)$ is again only a function of K_i/L_i, but in addition $F(A_i, L_i, K_i) \equiv H_1(A_i) \phi(L_i, K_i)^\alpha$, where ϕ is increasing in both of its arguments and exhibits constant returns to scale.

[10] In particular, as discussed in Section 3, under the pre-PPS system, Medicare-related capital and labor expenses were reimbursed in proportion to Medicare's share of patient days or charges (see Newhouse, 2002, p. 22).

[11] The assumption that $s_L < 1$ and $s_K < 1$ ensures that, at the margin, labor and capital costs are always positive for the hospital. In fact, all we need is that $m_i s_L < 1$ and $m_i s_K < 1$, so in practice when $m_i \leq \bar{m}$ for some $\bar{m} < 1$, we can have $s_L > 1$ and $s_K > 1$. The case in which there is true *cost plus* reimbursement whereby the hospital makes money by hiring more inputs is discussed in Appendix B.

The Inada and the differentiability assumptions imply that these first-order conditions are necessary, and the decreasing returns (strict joint concavity) of F implies that they are sufficient. Taking the ratio of these two first-order conditions we have

$$\frac{F_K\left(A_i, L_i^f, K_i^f\right)}{F_L\left(A_i, L_i^f, K_i^f\right)} = \frac{(1 - m_i s_K) R}{(1 - m_i s_L) w}, \tag{6}$$

which shows that the relative input choices of the hospital will be similar to that of an unregulated firm (hospital) with the same production technology, except for the relative generosity of capital and labor reimbursements. It is an immediate implication of (6) combined with decreasing returns that a decline in s_K/s_L, which corresponds to capital reimbursements becoming less generous relative to labor reimbursements, or an increase in the relative price of capital, R/w, will reduce K_i/L_i. The impact of changes in m_i on K_i/L_i will depend on whether s_K is greater or less than s_L. In the former case, capital is favored relative to labor, so higher m_i will be associated with greater capital intensity.

2.1.3 Partial Cost Reimbursement Regulation

Our main interest is to compare the full cost reimbursement regulation regime described above, which is a stylized description of the regulation policy before PPS, to the partial cost reimbursement that came with PPS. As described above, under this new regime, capital continues to be reimbursed as before, but labor reimbursements cease, and instead, hospitals receive additional payments from Medicare for health services provided to Medicare patients. We model this as an increase in q to $(1 + \theta m_i) q$, where $\theta > 1$ incorporates the fact that the extent to which a hospital receives the subsidy is also a function of its Medicare share.[12]

Now the maximization problem of hospital i is

$$\max_{L_i, K_i} \pi^p(i) = (1 + \theta m_i) qF(A_i, L_i, K_i) - wL_i - (1 - m_i s_K) RK_i. \tag{7}$$

Once again, the first-order necessary and sufficient conditions are

$$(1 + \theta m_i) qF_L(A_i, L_i^p, K_i^p) = w, \text{ and} \tag{8}$$

$$(1 + \theta m_i) qF_K(A_i, L_i^p, K_i^p) = (1 - m_i s_K) R, \tag{9}$$

[12] In practice, the price subsidy under PPS is a function of Medicare (diagnosis-adjusted) admissions. Modeling it as a function of the Medicare share, m_i—which corresponds roughly to Medicare share of total output (see Section 2.2)—is a simplifying assumption, with no major effect on our theoretical results.

where the superscript p refers to partial cost reimbursement. These first-order conditions jointly imply

$$\frac{F_K\left(A_i, L_i^p, K_i^p\right)}{F_L\left(A_i, L_i^p, K_i^p\right)} = \frac{\left(1 - m_i s_K\right) R}{w}. \tag{10}$$

Comparison of (10) to (6) immediately yields the following result (proof in Appendix A):

Proposition 1 *The move from full cost reimbursement to partial cost reimbursement will increase capital-labor ratio, i.e.,*

$$\frac{K_i^p}{L_i^p} > \frac{K_i^f}{L_i^f}. \tag{11}$$

In addition, if $F\left(A_i, L_i, K_i\right)$ is homothetic in L_i and K_i, then this effect is stronger for hospitals with greater Medicare share, i.e.,

$$\partial\left(\frac{K_i^p/L_i^p}{K_i^f/L_i^f}\right)/\partial m_i > 0. \tag{12}$$

This proposition is the starting point for our empirical work. It shows that the move from full to partial cost reimbursement should be associated with an increase in capital-labor ratios. Moreover, equation (12) provides an empirical strategy to investigate this effect by comparing hospitals with different Medicare shares (especially using the pre-reform period).

Next, we would like to know the impact of the change in regulation regime on the level of inputs and the total amount of health services. It is clear that the results here will depend on the generosity of the price subsidy (price cap) $\theta > 0$. We can obtain more insights by focusing on the case where the price cap, θ, is sufficiently low. This case is particularly relevant, since, as the empirical work below will show, the price cap appears to have been less than sufficient to overturn the effects of decreased cost subsidies. The existing evidence is also consistent with a relatively low price cap.[13]

We focus on the extreme case where $\theta = 0$ (clearly, by continuity, the same results apply when θ is sufficiently small around zero). In this case, we can simply analyze the effect of the change in the cost reimbursement regime as comparative statics of s_L; a reduction in s_L from positive to zero is equivalent to a change in regulation regime from full cost reimbursement the partial cost reimbursement.

[13] The qualitative description of the institutional details of PPS suggests a relatively low level of the price cap, 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 cap.

Proposition 2 *Suppose that $\theta = 0$, and let $L_i(s_L)$ and $K_i(s_L)$ be the optimal choices for hospital i at labor subsidy rate s_L. Then*

$$\frac{dL_i(s_L)}{ds_L} = \frac{-m_i F_{KK}}{F_{LL}F_{KK} - (F_{LK})^2} > 0. \tag{13}$$

Moreover, let $F(A_i, L_i, K_i)$ be homogeneous of degree $\alpha < 1$ in L_i and K_i, i.e., $F(A_i, L_i, K_i) = H_1(A_i)\,\phi(L_i, K_i)^{\alpha}$, with $\phi(\cdot,\cdot)$ exhibiting constant returns to scale. Let the (local) elasticity of substitution between capital and labor of the $\phi(\cdot,\cdot)$ function be σ_ϕ. Then

$$\frac{dK_i(s_L)}{ds_L} \lesseqqgtr 0 \text{ if and only if } \frac{1}{1-\alpha} \lesseqqgtr \sigma_\phi. \tag{14}$$

This proposition, which is also proved in Appendix A, shows that when the price cap is not very generous, the firm will respond to the switch from full to partial cost reimbursement by reducing its labor input, i.e., $dL_i(s_L)/ds_L > 0$ (since the move from positive to zero s_L corresponds to the switch to partial cost reimbursement). Moreover, it shows the close correspondence between the Medicare share, m_i, and this response, which is crucial for our empirical strategy.

Nevertheless, it is noteworthy that even in this case, capital inputs may increase, i.e., $dK_i(s_L)/ds_L \leq 0$ is possible. Whether they do so or not depends on the amount of "decreasing returns" to labor and capital, which is measured by the α parameter, and the elasticity of substitution, σ_ϕ. If $\sigma_\phi < 1$, so that labor and capital are gross complements in the ϕ function, capital will always decline as well. Similarly, if $\alpha = 1$, so that there are constant returns to scale to capital and labor jointly, again, capital will always decline. However, if $\alpha < 1$ and there is sufficient substitution between labor and capital, i.e., $\sigma_\phi > 1$, the firm can (partially) make up for the decline in its labor demand by increasing its capital inputs.

This is an important result both for understanding the response of capital inputs to an increase in the cost of labor in general, and for our specific case. The general relevance of this result stems from the *labor push theory of innovation* suggested by Hicks (1932) and Habakkuk (1962) as discussed in the Introduction. Despite a lengthy literature on this subject, there is still no agreement on the relevance of these ideas, especially since in the standard neoclassical growth model with constant returns to scale, this can never happen.[14] Proposition 2, on the other hand, shows that this result is possible when there are diminishing returns (either in terms of production technology or revenues) and when capital and labor are sufficiently

[14] This is obvious in Proposition 2, because of constant returns to scale, i.e., $\alpha = 1$. Alternatively, with constant returns to scale in labor and capital, the Euler theorem implies that $F_{LK} > 0$, so (32) immediately yields $dK_i(s_L)/ds_L > 0$.

substitutable. The specific interest of this result for our investigation comes from the fact that we are interested in how capital and technology (which is often embodied in capital) will respond to the change in regulation regime. This issue is discussed in greater detail next.

2.1.4 Technology Choices

The overall amount of capital inputs used by the firm is a combination of capital *embodying* new technologies and other types of capital, such as structures (e.g., buildings). These different types of capitals may respond differentially to the change in regulation. To study how technology will respond to the regulation regime, we now model technology choices.

Suppose that technology is always embodied in capital, and it can be measured by a real number, i.e., $A_i \in \mathbb{R}$, as specified by the production functions in (1) or (2). In particular, let us posit that there is a large number of (perfectly substitutable) technologies that can be adopted by the firm, each indexed by $x \in [0, \infty)$. Technology x requires a capital outlay of $\kappa(x)$.[15] We rank technologies such that $\kappa(x)$ is increasing. Furthermore, to simplify the analysis, let us assume that $\kappa(\cdot)$ is continuously differentiable. Since the productivity of the firm depends on how many of these technologies are adopted, i.e., on A_i, the firm will adopt low x technologies before high x technologies, i.e., there will exist a cutoff level x_i^* such that firm i adopts all technologies $x \leq x_i^*$, and moreover, clearly $x_i^* \equiv A_i$. Hence the capital cost of technology for hospital i when it adopts technology A_i will be

$$K_{a,i} \equiv \int_0^{A_i} \kappa(x)\, dx, \tag{15}$$

which is in addition to its capital costs for structures. Note from (15) that the marginal cost of adopting technology A_i is $\kappa(A_i)$ (from Leibniz's rule), and moreover, since $\kappa(x)$ is increasing, this marginal cost is increasing in A_i.

Naturally, there may be other non-technological differences in productivity across firms, but we ignore those here for simplicity (these can be easily introduced). Since we now allow for the adoption of new technologies embodied in capital, the remaining capital is interpreted as "structures" capital and denoted by $K_{s,i}$. Hence, we write

$$F(A_i, L_i, K_{s,i}) = \psi(A_i, L_i)^{\beta} K_{s,i}^{\eta} \tag{16}$$

[15] In practice, new technologies may differ in their productivity and may also require both capital and labor inputs for their adoption and operation. In the latter case, changes in the relative prices of capital and labor will also affect which technologies are more likely to be adopted. We do not model these issues explicitly both to simplify the analysis and also because we have no way of measuring the relative capital intensity of technologies in our empirical work.

where $\eta \in [0, 1-\beta)$ and ψ exhibits constant returns to scale, which imposes homogeneity of degree $\beta < 1$ between A_i and L_i. This assumption is reasonable when the remaining capital expenditures are interpreted as structures capital. The rest of the setup is unchanged.

Once again, since for arbitrary θ's, total output (health services) and inputs can increase or decrease, we focus on the case of $\theta = 0$. In this case, we have the following result mirroring Proposition 2 (again, the proof is in Appendix A).

Proposition 3 *Suppose that $\theta = 0$ and the production function is given by (16) with $\psi(\cdot,\cdot)$ exhibiting constant returns to scale. let $L_i(s_L)$, $A_i(s_L)$, $K_{a,i}(s_L)$ and $K_{s,i}(s_L)$ be the optimal choices for hospital i at labor subsidy rate s_L. Let ε_ψ be the (local) elasticity of substitution between L_i and A_i in the function $\psi(\cdot,\cdot)$. Then we have*

$$\frac{dL_i(s_L)}{ds_L} > 0 \text{ and } \frac{dK_{s,i}(s_L)}{ds_L} > 0. \tag{17}$$

and

$$\frac{\partial K_{a,i}(s_L)}{\partial s_L} \lesseqqgtr 0 \text{ and } \frac{\partial A_i(s_L)}{\partial s_L} \lesseqqgtr 0 \text{ if and only if } \frac{1-\eta}{1-\beta-\eta} \lesseqqgtr \varepsilon_\psi. \tag{18}$$

This proposition generalizes Proposition 2 to an environment with labor, capital and technology choices, and is the starting point of our empirical analysis of technology choices. It indicates that the same kind of comparison between the elasticity of substitution and returns to scale also guides whether or not technology adoption will be encouraged by the change in the regulation regime. In this case, the comparison is between the elasticity of substitution between technology (or capital embodying the new technology) and labor, ε_ψ, and a composite term which captures both decreasing returns to labor and technology and to the structures capital. In particular, when $\eta = 0$, the condition in (18) is equivalent to that in (14), but when $\eta > 0$, this condition becomes harder to satisfy, because structures capital also adjusts, leaving less room for technology adjustment. Nevertheless, the qualitative insights are similar, and indicate that the essence of the labor push theory will apply with sufficient decreasing returns and a sufficiently large degree of substitution between technology and labor.

The important implication for our empirical work is that even if the price cap under the partial regulation regime is not very generous, so that overall labor inputs decline, technology-labor substitution may increase technology adoption. Naturally, technology and capital expenditures on technology are more likely to increase when θ is positive (i.e., with $\theta > 0$, they may increase even when $\varepsilon_\psi < (1-\eta)/(1-\beta-\eta)$). Nevertheless Proposition 3 gives a useful benchmark and emphasizes the role of decreasing returns to scale and the substitutability between labor and technology (or capital).[16]

Another interesting implication of Proposition 3 is that we could have a configuration in which expenditures on technology (and overall technology adoption) increase with the switch from full cost reimbursements to PPS, while total capital expenditures may decrease or remain unchanged, because they also include the component on structures expenditure. This is relevant for interpreting the empirical results below.

2.1.5 Skill Composition of Employment

Finally, in our empirical work we will also look at changes in the composition of the workforce, in particular, of nurses. To do this, the production function can be generalized to

$$F(A_i, U_i, S_i, K_i) \tag{19}$$

where U_i denotes unskilled labor (nurses) while S_i denotes skilled labor (nurses). As is standard, an increase in capital/labor ratio and technology adoption will increase the ratio of skills to unskilled labor as long as technology and/or capital is more complementary to skilled than unskilled labor. To state the result here in the simplest possible form, suppose that A_i is fixed, so that the main effect of the change in regulation will work through an increase in the capital stock overall (including equipment as well as structures capital). Then the following proposition is immediate (proof omitted):

Proposition 4 *Suppose that $F(A_i, U_i, S_i, K_i)$ is homothetic in U_i, S_i and K_i, and denote the (local) elasticity of substitution between U_i and K_i by σ_U and the elasticity of substitution between S_i and K_i by σ_S. Then*

$$\frac{S_i^p}{U_i^p} \gtreqless \frac{S_i^f}{U_i^f} \text{ if and only if } \sigma_S \lesseqgtr \sigma_U.$$

This proposition therefore shows that when capital is more complementary to skilled than unskilled labor, the removal of the implicit subsidy to labor involved in the change from full cost reimbursements to partial cost reimbursement will increase the skill composition of hospitals. A similar proposition could be stated for the case in which the main margin of adjustment is

[16] In the health services sector, there is a natural substitution between technology and labor, which takes place by varying the length of stay in hospital. Use of more high-tech equipment saves on labor by allowing patients to leave earlier, which amounts to substituting technology for labor. We investigate this issue empirically below.

technology (embodied in capital), which would correspond to technology-skill complementarity rather than capital-skill complementarity.

As discussed in the Introduction, the existing view in the literature is that capital and technology are more complementary to skilled labor than unskilled labor. Changes in the skill composition of affected hospitals' workforces therefore gives us an indirect way of verifying the results on capital-labor ratios and technology adoption. Moreover, despite this general belief, there are few empirical estimates of capital-skill or technology-skill complementarity, so this proposition suggests that PPS might provide us with useful evidence on the extent of such complementarities.

2.1.6 Price Cap Regulation

Our framework also enables us to investigate the implications of a change from partial or full cost reimbursement to "pure" price cap regulation. The latter naturally corresponds to a situation in which there is no longer any reimbursement of capital and labor, and the revenue function of a hospital with Medicare share m_i is simply $\left(1+\theta' m_i\right) qF\left(A_i, L_i, K_i\right)$, where we can think of $\theta' > \theta$ so that the pure price cap regime is more generous in terms of reimbursement for health services to Medicare patients. The maximization problem of hospital i then becomes

$$\max_{L_i, K_i} \pi^c(i) = \left(1+\theta' m_i\right) qF\left(A_i, L_i, K_i\right) - wL_i - RK_i, \tag{20}$$

where we now use superscript c to denote choices under pure price cap.

The following result is immediate (proof omitted):

Proposition 5 *Consider a move from partial cost reimbursement regulation to pure price cap. Then we have*

$$\frac{K_i^p}{L_i^p} > \frac{K_i^c}{L_i^c},$$

i.e., capital-labor ratio will decline following the change in regulation. In the case of a move from full cost reimbursement regulation to pure price cap, we have

$$\frac{K_i^c}{L_i^c} \gtreqless \frac{K_i^f}{L_i^f} \text{ if and only if } s_L \gtreqless s_K,$$

i.e., capital-labor ratio will decline following the change in regulation only if the full cost reimbursement regime treated capital more generously than labor.

As with the comparison of full and partial cost reimbursement, there are no unambiguous results on the overall level of inputs without specifying the level of θ' relative to θ. But a similar analysis to the one above shows that if θ' is sufficiency close to θ, the total amount of capital input (and technology) will decline when there is a change from partial cost reimbursement to price cap. Moreover, exactly the same type of analysis also establishes that the total amount of labor will increase or decrease in this case depending on the elasticity of substitution between capital and labor and the extent of decreasing returns. Since the move from full to partial cost reimbursement is our main focus in this paper, we do not spell out these results.

2.2 Choice of Medicare Share

The analysis so far treated the Medicare share of hospital i, m_i, as exogenously given. We now briefly discuss how this can be endogenized without affecting our main results.

Suppose that the hospital produces two distinct "products," Medicare health services and non-Medicare health services (the latter may also include outpatient Medicare, which is reimbursed differently). Let the production functions for these two products be

$$F_m\left(A_{m,i}, L_{m,i}, K_{m,i}\right) \text{ and } F_n\left(A_{n,i}, L_{n,i}, K_{n,i}\right),$$

with respective prices q_m and q_n, and exogenous technology terms $A_{m,i}$ and $A_{n,i}$, and let

$$m_i = \frac{F_m\left(A_{m,i}, L_{m,i}, K_{m,i}\right)}{F_m\left(A_{m,i}, L_{m,i}, K_{m,i}\right) + F_n\left(A_{n,i}, L_{n,i}, K_{n,i}\right)}, \tag{21}$$

be the Medicare share of total output. Alternatively, we could have defined m_i as the Medicare share of total operating expenses, $m_i = L_{m,i}/\left(L_{m,i} + L_{n,i}\right)$, or the Medicare share of capital expenses, $m_i = K_{m,i}/\left(K_{m,i} + K_{n,i}\right)$, in both cases with identical results.

The maximization problem of the hospital under full cost reimbursement is:

$$\begin{aligned} \max_{\substack{L_{m,i}, K_{m,i},\\ L_{n,i}, K_{n,i}, m_i}} \pi^m(i) &= q_m F_m\left(A_{m,i}, L_{m,i}, K_{m,i}\right) + q_n F_n\left(A_{n,i}, L_{n,i}, K_{n,i}\right) \\ &\quad - \left(1 - m_i s_L\right) w \left(L_{m,i} + L_{n,i}\right) - \left(1 - m_i s_K\right) R \left(K_{m,i} + K_{n,i}\right), \end{aligned} \tag{22}$$

subject to (21).

This maximization problem can be broken into two parts. First, maximize $q_m F_m\left(A_{m,i}, L_{m,i}, K_{m,i}\right) + q_n F_n\left(A_{n,i}, L_{n,i}, K_{n,i}\right)$ with respect to $L_{m,i}, K_{m,i}, L_{n,i}$ and $K_{n,i}$ for given m_i and subject to (21) and to the constraints that $L_i = L_{m,i} + L_{n,i}$ and $K_i = K_{m,i} + K_{n,i}$. Let the value of the solution to this problem be $qF\left(L_i, K_i, m_i\right)$, which only depends on the total amount of labor $L_i = L_{m,i} + L_{n,i}$ and total amount of capital $K_i = K_{m,i} + K_{n,i}$. Once this first step of maximization is carried out, the full maximization in (22) can be obtained as the solution to

$$\max_{L_i,K_i,,m_i} \tilde{\pi}^m (i) = qF (L_i, K_i, m_i) - (1 - m_i s_L) wL_i - (1 - m_i s_K) RK_i.$$

Similarly, with the same assumptions as in subsection 2.1, the maximization problem under the partial cost reimbursement regulation regime is

$$\max_{L_i,K_i,,m_i} \tilde{\pi}^p (i) = (1 + qm_i) F (L_i, K_i, m_i) - wL_i - (1 - m_i s_K) RK_i.$$

This implies that the analysis in subsection 2.1 can be carried out as before, with the only addition that now m_i is also a choice variable. The following proposition is then an immediate generalization of Proposition 1 (proof in Appendix A):

Proposition 6 *Let the Medicare shares with full and partial cost reimbursement be, respectively, m_i^f and m_i^p, then as long as*

$$\frac{m_i^f - m_i^p}{m_i^f (1 - m_i^p)} < \frac{s_L}{s_K} \tag{23}$$

the move from full the partial cost reimbursement regulation increases the capital-labor ratio, i.e.,

$$\frac{K_i^p}{L_i^p} > \frac{K_i^f}{L_i^f}. \tag{24}$$

Notice that (23) is automatically satisfied if $m_i^f \leq m_i^p$, and we obtain the same results as in Subsection 2.1 in this extended model with endogenous Medicare share.

Moreover, a similar analysis to the one in Subsection 2.1 immediately establishes that if θ is close enough to zero (i.e., if the partial cost reimbursement is not very generous), we would have $m_i^f > m_i^p$. In this case, the additional implication for the empirical work would be that the Medicare share should decline after the introduction of PPS. Since, as mentioned above, our evidence on the change in the total amount of labor (operating expenses) suggests that PPS was less generous than the full cost reimbursement regime, this is an interesting implication which we will also investigate empirically; it provides a consistency check for the other results suggesting that the price cap under PPS was not very generous. It is also useful to note that even when $m_i^f > m_i^p$, (23) is not very restrictive, so empirically we would expect the capital-labor ratio to increase after the introduction of PPS (i.e., following the transition from full to partial cost reimbursement) even if the Medicare share is observed to decline.

3 Overview of Medicare Reimbursement Policies

The Medicare Prospective Payment System (PPS) was introduced in October 1983 (i.e. 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, where the share was proportionate to Medicare's share of patient days in the hospital (OTA, 1984, Newhouse, 2002, p. 22). By contrast, under PPS, hospitals are reimbursed a fixed amount for each patient based on his 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, in practice, 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 eight yeas of PPS, capital costs continued to be fully passed back to Medicare under the old cost-based reimbursement system. Capital reimbursement only became fully prospective in 2001; thus for almost its first 20 years, the Medicare Prospective Payment System continued to reimburse capital costs at least partly on the margin.[17] The reason for the differential treatment of operating and capital costs appears to be the greater difficulty in designing a prospective payment system for capital (CBO, 1988, Cotterill, 1991). This explains the use of such partial price caps in other regulated industries as well (Joskow, 2005).

The PPS reform therefore is an example of a switch from *full cost reimbursement* to *partial cost reimbursement,* as described in Section 2. However, in the voluminous economics literature on Medicare PPS, we have found only two references to the differential treatment of capital (Newhouse, 2002, p. 30, Weisbrod, 1991, p. 527). 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

[17] The original legislation specified that the treatment of capital costs would be unchanged for the first three 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).

associated with declines in hospital spending and utilization, but not with substantial adverse health outcomes. However, much of this literature is based on simple pre-post comparisons. Important exceptions include Feder et al.'s (1987) study of the impact of PPS on spending and Staiger and Gaumer (1990) and Cutler's (1995) study of the impact of PPS on health outcomes. Staiger and Gaumer (1990) 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 those in this literature that there has been a decrease in hospital expenditures and in utilization associated with PPS, but, to our knowledge, our work is the first to investigate the impact of PPS on labor and capital inputs and the skill composition of the workforce.

Finally, there is a small empirical literature studying the impact of PPS on technology adoption. Using mostly pre-post comparisons, it has found little conclusive evidence of an impact of PPS on technology adoption (Prospective Payment Assessment Commission, 1988, 1990, Sloan et al., 1988).[18] To our knowledge, ours is the first theoretical or empirical study to suggest (and document) that PPS might have been associated with an overall *increase* in technology adoption.

4 Data and Descriptive Statistics

4.1 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. These data have been widely used to study the hospital sector and are considered to be of high quality. PPS took effect at the start of each hospital's fiscal year on or after October 1, 1983. Our data consist of four years prior to PPS (fiscal years 1980 - 1983) and three years post PPS (fiscal years 1984 - 1986). In all of our empirical work, we interpret the year of the data as corresponding to the hospital's fiscal year.[19]

We restrict our analysis to the first three years of PPS, during which the treatment of

[18] These studies—like our work below—focus on the adoption of previously existing technologies. By contrast, a well-known study by Kane and Manoukian (1989) looks at the impact of PPS on a newly invented technology—the cochlear implant—and finds substantial negative effects on adoption. They argue that the effective reimbursement rate for this new technology was set below the break-even level.

[19] In practice, the data may consist of somewhat less than three years post PPS since only about one quarter of hospitals begin their fiscal year on October 1. In addition not all hospitals report data for the 12-month period corresponding to their fiscal year. We discuss these issues in more detail in the interpretation of the empirical results below.

capital was specified in advance, and do not extend the analysis to cover the subsequent period of uncertainty concerning the treatment of capital (footnote 17 provides more detail on the initial treatment of capital and the subsequent period of uncertainty). We also exclude from the analysis four states (MA, NY, MD and NJ) which 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 (Health Care Financing Administration, 1986, Health Care Financing Administration, 1987, Antos, 1993, MHA, 2002). These four states contain about 10 percent of the nation's hospitals, leaving a sample of about 6,200 hospitals per year.[20]

The data contain information on total input expenditures and various components of expenditures, admissions, patient days, employment and various components of employment, and a series of binary indicator variables for whether the hospital has a variety of different technologies. The expenditure and utilization data for year t are in principle measured for the twelve-month reporting period from October 1, t-1 through September 30, t; the employment and technology variables are supposed to be measured as of September 30, t. Note that hospital employment and payroll consist of nurses, technicians, therapists, administrators, and other support staff; most doctors are not included as 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 (GAO, 1986, OTA, 1984, Cotterill, 1991), each of which we can identify in the AHA data.[21] Since changes in interest expenses may reflect financing changes rather than real changes in inputs, we focus primarily on depreciation expenses (which are about two-thirds of combined interest and depreciation expenses). Medicare uses straight-line depreciation to

[20] Cutler (1995) uses MA as a control state relative to other New England states in his study of the impact of PPS on health outcomes, as PPS was only introduced in MA in FY 1986. Because Medicare and Medicaid experimented with alternative forms of rate setting in MA between FY 1982 and FY 1985 (Health Care Financing Administration, 1987), MA is not suitable to be used as a control state for our analysis of the effect of relative factor price changes resulting from PPS (although these do not necessarily pose a problem for Cutler's analysis of the impact of PPS on health outcomes).

[21] 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, Prospective Payment Assessment Commission, 1992, Medicare Payment Advisory Commission, 1999).

reimburse hospitals for the depreciation costs of structures and equipment (CBO, 1988). The estimated useful life of an asset is determined by the American Hospital Association; during the time period we study, it ranged from 4 to 40 years depending on the asset; lives of 5 and 10 year tend to be the most common (AHA, 1983). Depreciation expenses therefore measure past and current capital expenditures rather than the capital stock, which would be the ideal measure. Nevertheless, since the cost of capital and equipment prices should not vary across hospitals, 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. Depreciation expenses are on average about 4.5 percent of operating expenses (see Table 1).

4.2 Descriptive Statistics and Time Series Evidence

Table 1 gives the basic descriptive statistics for our key variables over the entire sample. Changes in these variables over time are depicted in Figures 1-3.

Figure 1 shows the simple time series average of hospital capital-labor ratio (depreciation share). Consistent with Proposition 1, the time series displays a striking increase in the average capital-labor ratio at the time of PPS's introduction (FY 1984) both in absolute terms and relative to the pre-existing time series pattern. Proposition 2 suggests that if the level of the price cap θ is sufficiently non-generous, labor inputs should fall, but that even in this case capital inputs may rise, fall, or remain unchanged. The time series results are broadly consistent with this and show a pronounced decrease in labor inputs (real operating expenditures) relative to the pre-existing trends (Figure 2). They also show no evidence of a deviation in capital inputs (real depreciation expenditures) from the pre-existing time series trend (Figure 3).[22]

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

[22] To match the emprical work below, the time series in Figures 2 and 3 are presented on a log scale; in practice, the pattern is similar if we look at absolute levels.

5 Econometric Framework

The motivating theory developed in Section 2 suggests an empirical strategy for detecting the effects of PPS reform based on variation across hospitals in their (pre-PPS) Medicare share, m_i. Proposition 1 indicates that the regulatory change should be associated with an increase in the capital-labor ratio for all affected hospitals (i.e., for all hospitals with $m_i > 0$), but with a larger effect in hospitals with a higher m_i (see equation (12)). Based on this reasoning, our basic estimating equation is

$$y_{it} = \alpha_i + \gamma_t + \mathbf{X}'_{it} \cdot \boldsymbol{\eta} + \beta \cdot (POST_t \cdot m_i) + \varepsilon_{it}, \tag{25}$$

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 in Proposition 1. We will later use the same framework to investigate the responses of a number of other outcomes.

In our estimating equation (25), 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 time-varying covariates. These other time-varying covariates 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 $(POST_t \cdot m_i)$ with coefficient β. Here $POST_t$ is a dummy variable which takes the value equal to 1 for the three post-PPS years (1984-1986). A useful variant of this equation is

$$y_{it} = \alpha_i + \gamma_t + \mathbf{X}'_{it} \cdot \boldsymbol{\eta} + \beta \cdot (POST_t \cdot m_i) + \phi \cdot (d_{1983} \cdot m_i) + \varepsilon_{it}, \tag{26}$$

where d_{1983} is a dummy for the year 1983. The interaction term $(d_{1983} \cdot m_i)$ acts as a pre-specification 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 will also estimate a more flexible version of these equations of the form

$$y_{it} = \alpha_i + \gamma_t + \mathbf{X}'_{it} \cdot \boldsymbol{\eta} + \sum_{t \geq 1981} \beta_t \cdot m_i + \varepsilon_{it}. \tag{27}$$

Relative to (25) or (26), the model in (27) 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, p. 275 for details and for how such a robust variance estimator takes care of potential serial correlation with fixed effects estimators). In practice, this does not have much of an effect on the standard errors.

A key question is how to measure m_i empirically. In the theoretical section, this variable corresponds to the Medicare share of total revenue or of total operating expenses. Since in practice Medicare reimbursed for hospital expenses in the pre-PPS regime based on Medicare's share of patient days in the hospital (Newhouse, 2002, p. 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 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 distribution looks normal, except for the mass point of almost 15 percent of hospitals which we have coded as having zero Medicare share. This reflects that 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, p. 27). The exemption presumably stems from the extremely low Medicare share of these hospitals.[23] For our purposes, we code their m_i as 0 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 non-zero share hospitals, or using only the variation in m_i among hospitals coded with a non-zero m_i.

The identifying assumption in estimating equations (25), (26), and (27) is that, absent 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 across hospitals. Indeed, in the cross-section prior to PPS, a larger m_i is correlated with lower operating expenditures and higher depreciation shares (results not shown).[24] Any fixed

[23] On average, the actual Medicare share for these hospitals is only 9 percent in 1983, compared to 45 percent for other hospitals.

[24] These and other results mentioned in the paper, but not shown in the tables are available upon request from the authors.

Prior to PPS, cost reimbursement of capital was relatively more generous than that of labor. The cross-sectional relationship between a higher Medicare share and a higher capital-labor ratio prior to PPS is consistent with the results in Section 2 that, under full cost reimbursement, if capital reimbursement is more generous than labor reimbursement, a higher Medicare share will be associated with a higher capital-labor ratio.

differences across hospitals will be absorbed by the hospital fixed effects, the α_i's. However, such systematic differences raise concerns about whether absent the introduction of PPS in FY 1984, hospitals with different m_i would have experienced similar *changes* in the outcomes of interest. Equations (26) and (27) 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 systematic evidence of such pre-existing trends, supporting our identifying assumption.

Motivated by the theoretical predictions, we estimate equations (25), (26), and (27) 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. A level specification would constrain the outcomes to grow by the same absolute amount in each year, which would be inappropriate given the considerable variation in size across hospitals.

6 Main Results

6.1 Results on Capital-Labor Ratio

Proposition 1 suggests that the move from full cost to partial cost reimbursement will increase the capital-labor ratio. We investigated 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, (25). The $POST_t$ variable is simply a dummy for the three years in which PPS is in effect in our sample (1984-1986). In this specification, the coefficient β on the key interaction term ($m_i \cdot POST_t$), 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 three 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) estimates equation (26) in order to investigate whether the differential growth in the capital-labor ratio between high and low Medicare share hospitals was present before the introduction of PPS. The estimate of the key parameter, β, is essentially unchanged, while 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 through 1982, hospitals with a larger m_i 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 validity of the identifying assumption that absent the introduction of PPS, hospitals with different Medicare shares would have experienced similar changes in their capital and labor demands.

Column (3) shows the results from estimating the more flexible equation (27) 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 years 1981 or 1983, but there is a one-time downward blip in 1982. 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 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 twelve month period from October 1, *t-1* to September 30, t; in any given year, about half appear to instead report data for the twelve-month period corresponding to their fiscal year. This also contributes to a staggered implementation of PPS in the data.[25] However,

[25] In practice, it is difficult to exploit this potential source of additional empirical variation because there is

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,

$$y_{it} = \alpha_i + \gamma_t + \mathbf{X}'_{it} \cdot \boldsymbol{\eta} + \tilde{\beta} \cdot \left(\sum_{t \geq 1984} (t - 1983) \cdot m_i \right) + \phi \cdot (d_{1983} \cdot m_i) + \varepsilon_{it}, . \tag{28}$$

which imposes a linear structure on the post-PPS effects. This equation has the advantage of summarizing the post-PPS patterns more parsimoniously than equation (27).

Columns (4) and (5) estimate equation (28) with and without the pre-specification test term, $(d_{1983} \cdot m_i)$. In both cases, there is a very precisely estimated coefficient of $\tilde{\beta}$ 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 similar calculation to 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 its capital-labor ratio.[26]

6.2 Results on Labor and Capital Inputs and Medicare Share

Proposition 2 suggests that if the generosity of the price cap θ is not very high, labor inputs should decline with the change from full to partial cost reimbursement. Table 3 investigates the differential change in (log) labor inputs (log operating expenses) across hospitals with different pre-PPS Medicare shares; it reports results from estimating equations (25), through (28) with this alternative dependent variable. Consistent with Proposition 2, the results suggest that the

considerable year-to-year variation in a given hospital's reporting period.

[26] Our estimate of the magnitude of the response of the capital-labor ratio to the change in regulatory regime may be affected by hospitals' expectations that continued reimbursement of capital costs might be temporary. A priori, 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.

move from full cost to partial cost reimbursement was associated with a decline in labor inputs. Once again, the estimates are quite precise. For example, the estimate of β, the coefficient on the interaction term $(m_i \cdot POST_t)$, in column (1) is -0.141 (standard error = 0.016). Column (2) shows no evidence of a pre-existing trend. These estimates suggest that during the first three years of PPS, there was a decline of about 5 percent ($\simeq 0.141 \times 0.38$) in labor inputs for an average Medicare share hospital.

The estimates in column (3) again suggest that the impact of PPS was increasing over the first three years in which it was in place. Correspondingly, the linear trend specifications in columns (4) and (5) also fit the data very well and produce precise estimates of about -0.07.[27] This implies that, during its first three years, the PPS reform was associated, on average, with an approximately 3 percent ($\simeq 0.07 \times 0.38$) decline per year in labor inputs. These specifications also show some evidence of a small and marginally statistically significant *increase* in operating expenditures in more affected hospitals in some of the pre-PPS years. Although this may raise concerns about the potential for mean reversion that may contaminate our estimate of the impact of PPS, Section 7 shows that the results are highly robust to a number of specification that flexibly deal with potential mean reversion issues.

Perhaps the most interesting theoretical suggestion in Proposition 2 is that even when the price cap θ is low enough that labor inputs decline, capital inputs need not decrease, and may in fact increase. Table 4 estimates our baseline models for log capital inputs (log depreciation expenses). The results indicate essentially no effect on capital inputs. The coefficient on the interaction term $(m_i \cdot POST_t)$ is always very small and typically statistically insignificant.[28] These results suggest that the decline in labor inputs was not associated with a corresponding decline in capital inputs, which is consistent with the results in Proposition 2 when there is sufficient substitutability between capital and labor.[29]

Finally, we note that we have interpreted the results for labor and capital inputs as consistent with the predictions of the theoretical model for the case when the price cap θ is relatively

[27] In addition to the possible lags in implementation and lags in adjustment discussed above, another potential explanation for the time pattern in the adjustment of labor inputs to PPS is that the level of the price cap θ was tightened after the first year of PPS (Coulam and Gaumer, 1991), which would naturally lead to further declines in labor inputs.

[28] Given the evidence of a decline in labor inputs (operating expenditures) and no change in capital inputs (depreciation expenditures) associated with PPS, we would also expect a decline in total hospital expenditures. We verified that this is indeed the case (results not reported to save space). This is consistent with similar empirical findings in the existing literature (see, e.g., Feder et al., 1987).

[29] Recall, however, from Proposition 3 that technology may increase even if total capital inputs do not increase, since total capital inputs include both capital embodying new technologies and other types of capital, such as structures. We investigate the impact of PPS on technology adoption in the next subsection.

low. As discussed in footnote 13, existing qualitative and empirical evidence supports our interpretation on these results in the context of a relatively low price cap. We can also provide some additional empirical evidence consistent with a relatively low level of the price cap. Specifically, section 2.2 showed that for a sufficiently low level of the price cap, the change from full to partial cost reimbursement should be associated with a decline in the Medicare share m_i. Table 5 reports results from regression analysis where the dependent variable is Medicare's share of patient days. To prevent a mechanical correlation between the cross-sectional variation, m_i, and the dependent variable, in this table, we define the right-hand side cross-sectional variation in m_i based on the hospital's m_i in 1980, and exclude 1980 from the analysis.[30] The point estimate in our preferred specification (column 5) is -0.032 (standard error = 0.003), which suggests that, for its first three years, PPS was associated with, on average, about a 1 percent ($\simeq 0.032 \times 0.38$) per year decline in the Medicare share of patient days. These results are consistent with past research, which has found that PPS was associated with substantial declines in Medicare patient days (Coulam and Gaumer, 1991), although to our knowledge ours are the first estimates of the impact of PPS on Medicare's *share* of total patient days.

6.3 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, 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, 2005). 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 total number of facilities, which provides one proxy for the A_i variable in the theoretical model

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 that they are available in Appendix Table A. They form an unbalanced panel. On average, a given facility is reported in the data for 4.6 out of the possible 7 years; only one-quarter of the technologies are in the data for all seven years. Moreover, as is readily apparent from even a cursory glance through Appendix Table A, the list encompasses a range of very different types of facilities. Given these two features of the data, we pursue two complementary approaches

[30] All of our previous results are robust to this alternative specification.

to analyzing the impact of the change from full to partial cost reimbursement on technology adoption.

Our first approach (reminiscent of the perfect substitutability across different technologies in the model) treats all facilities equally and estimates equations (25)-(28) 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 data). Our second approach estimates separate hazard models of the time to adoption (parallel to the time to "failure" in the typical hazard model) for specific technologies that are in the data for all of the years of our sample. We discuss this approach in more detail below.

6.3.1 Number of Facilities

In our first approach, the dependent variable is the raw count of the number of facilities of each hospital. The dependent variable ranges from 0 to 77 with an average of 25. Approximately 10 percent of the hospital-years in the sample have zero facilities. Table 6 shows the results. Panel A reports the OLS estimates. Since there are a large number of zero's, 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. However, since, as discussed above, we prefer a proportional estimator, Panel B reports the analogous set of results from the conditional fixed effects Poisson model (Hausman et al., 1984). This latter approach essentially amounts to assuming the following conditional expectation for the number of facilities for hospital i at time t, N_{it}, given the sample mean of the vector of covariates $\mathbf{X}_i$, $\bar{\mathbf{X}}_i$, for hospital i:

$$E\left[N_{it} \mid \alpha_i, \bar{\mathbf{X}}_i\right] = \exp(\alpha_i + \gamma_t + \mathbf{X}_{it}' \cdot \boldsymbol{\eta} + \beta \cdot (POST_t \cdot m_i) + \phi \cdot (d_{1983} \cdot m_i)). \quad (29)$$

Because this equation is nonlinear and cannot be estimated consistently with fixed effects, we follow Hausman et al. (1984), and estimate the conditional logit transformation of this equation with quasi maximum likelihood. More specifically, we estimate

$$E\left[N_{it} \mid \alpha_i, \bar{\mathbf{X}}_i, \bar{N}_i\right] = \frac{\exp(\gamma_t + \mathbf{X}_{it}' \cdot \boldsymbol{\eta} + \beta \cdot (POST_t \cdot m_i) + \phi \cdot (d_{1983} \cdot m_i))}{\sum_{\tau=1}^{T} \exp(\gamma_\tau + \mathbf{X}_{i\tau}' \cdot \boldsymbol{\eta} + \beta \cdot (POST_\tau \cdot m_i) + \phi \cdot (d_{1983} \cdot m_i))} \bar{N}_i, \quad (30)$$

where $\bar{N}_i$ is the average number of facilities for hospital i over the sample. This transformation removes the unobserved hospital effects, the α_i's, and enables consistent estimation (see Hausman et al., 1984, Wooldridge, 2002, pp. 674-676).

In practice, the results are not sensitive to whether we estimate OLS models or use the conditional fixed effect Poisson model in equation (30).[31] In either case, 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 facilities of affected hospitals.

The point estimate from the OLS specification in column (1) is 2.621, suggesting that, on average, the regulatory change is associated with an increase of about one new facility ($\simeq 0.2.621 \times 0.38$) in a hospital over its first three years; this corresponds to about a 4 percent increase over the average number of facilities in a hospital (which is about 25). The magnitude of the estimated effect is quite similar in the conditional fixed effect Poisson specification in column (6); the point estimate of 0.12 suggests that the introduction of PPS is associated with an approximately 5 percent ($\simeq 0.120 \times 0.38$) increase in the number of new facilities for the average Medicare share hospital over its first three years.

The results in Table 6 are also broadly supportive of our identifying assumption of no differential trends across hospitals in the number of facilities prior to PPS. Columns (3) and (8) show 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 between any of the other pre-PPS years 1981, 1982 or 1983. Although these findings raise potential concerns about mean reversion, once again our robustness analysis in Section 7 shows 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 most flexibly estimated specification (columns 3 or 8). In particular, 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 (OLS specification) or at least not rise from 1985 to 1986 (conditional fixed effect Poisson specification).

6.3.2 Hazard Models

A 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 of the years of our sample. We focus on 10 technologies

[31] The standard errors in the conditional fixed effect Poisson model have not yet been adjusted to allow for an arbitrary covariance matrix within each hospital over time. We plan to do so for the next version of the paper, and in the meantime have verified that a conditional fixed effect negative binomial model yields very similar results.

that were identified as "high tech" and analyzed as such by previous researchers (Cutler and Sheiner, 1998, Baker, 2001, and Baker and Phibbs, 2002), and that are present in our data in all years. Two of these technologies 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 two are other miscellaneous technologies (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 in both 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 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—constant—proportional hazard model of the form:

$$\lambda_t = \alpha \exp\left(\gamma_t + \phi \cdot d_{1983} \cdot m_i + \beta \cdot (POST_t \cdot m_i) + \mathbf{X}_i' \cdot \boldsymbol{\eta}\right), \tag{31}$$

where λ_t denotes the conditional probability that the hospital adopts a given technology 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.

Since we have at most a single transition (adoption) for each hospital, we cannot include hospital fixed effects as we have done in all of the prior analyses. 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 (non-speciality) hospital, whether it is short term, whether it is federal, whether it is located in an urban area, and a complete set of state fixed effects.[32]

Our second model is a Cox semi-parametric proportional hazard model, which allows for a fully flexible, non parametric baseline hazard λ_0, and is estimated by a transformation similar to that in equation (30)—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.

[32] In practice, conditional on including m_i and the square of m_i, the results are not sensitive to the inclusion of the additional baseline covariates.

Note also that reestimating our previous models dropping the hospital fixed effects and instead controlling for these covariates yields very similar results to those with hospital fixed effects (results not shown).

Table 7 reports the results from both models. To conserve space, we report results only from a specification similar to equation (26), which includes a single interaction between the Medicare share, m_i, and the post-PPS period dummy, $POST_t$ as well as the pre-specification test with the interaction between m_i and the dummy for the year 1983.[33] To illustrate the magnitude of our estimates, Table 7 also translates the hazard model coefficient on $POST_t \cdot m_i$ into the implied change in the proportion of hospitals who adopt the technology between 1981 and 1986 associated with changing m_i from its mean to zero. For this calculation, all other covariates are set at their mean.

Panel A of Table 7 reports the results from the exponential proportional hazard model, while Panel B reports results from the Cox proportional hazard model. On the whole, both panels show very similar results and suggest that the shift from full cost to partial cost reimbursement was associated with increased technology adoption.

Overall, the evidence in Table 7 suggests that PPS likely increased the adoption of 6 or 7 out of the 10 specific technologies.[34] For technologies, such as the cardiac catheterization and open heart surgery, which are used disproportionately by Medicare patients, our interpretation of the apparent increase in adoption associated with PPS is along the lines of Proposition 3, and relies on technology-labor substitution. Evidence potentially consistent with such technology-labor substitution is discussed in the next subsection. An impact of PPS on adoption of cardiac technologies is particularly interesting given the important role that the diffusion of these technologies appears to have played in both the rise in health care costs and the improvement in elderly life expectancy over the last decades (Cutler, 2003).

Other affected technologies, such as the neonatal intensive care unit and the organ transplant facilities, are likely to be used almost exclusively by non-Medicare patients. Our interpretation for these results is that they are driven by spillovers and complementarities between new technologies, or changes in the composition of effort by hospital managers across different products. We discuss this in further detail in subsection 6.6 below.

6.4 Technology-Labor Substitution

In view of Proposition 3, our finding that a switch to partial cost reimbursement is associated simultaneously with a decline in labor inputs and increased technology adoption suggests that

[33] As with the results for the total number of facilities, the results from hazard model estimates of individual technologies do not indicate that the impact of PPS grows continually over the three PPS years in our sample.

[34] Three of the technologies show , negative effects of PPS on adoption. However the estimated magnitude is both statistically and economically insignificant.

these technologies are substitutes for labor inputs (or operating inputs more generally). This raises the question of the mechanism by which these technologies substitute for labor.[35] While we cannot provide a definitive answer to this question, we provide some suggestive evidence of one natural mechanism of technology-labor substitution for hospitals, which is by using 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, Table 8 presents evidence that Medicare PPS is associated with declines in log average length of stay, defined as log(patient days/admissions).[36] This finding is consistent with those in many other studies, reviewed by Coulam and Gaumer (1991) and Cutler and Zeckhauser (2000), that also found a decline in length of stay associated with PPS.

The magnitude of the decline in log length of stay associated with PPS in Table 8 is quite similar to the estimated decline in Medicare share associated with PPS in Table 5. This suggests that, although we cannot separately examine the impact of PPS on length of stay among Medicare patients (because we do not observe admissions numbers separately for Medicare and non-Medicare patients), the decline in length of stay associated with PPS is likely to have been concentrated among Medicare patients.

6.5 Changes in Skill Composition

Finally, Proposition 4 suggests that when technology (or capital) is more complementary to skilled than to unskilled labor, a consequence of an induced increase in technology (or in the capital-labor ratio) will be a change in the composition of the workforce towards more skilled employees.

Our data permit us to investigate this prediction by looking at changes in the composition of nurse employment. In particular, we can separately identify full time equivalent employment of two types of nurses in the data, Registered Nurses (RN's) and Licensed Practical Nurses (LPN's). Together these constitute about one-quarter of total fulltime-equivalent hospital employment, with RN's forming 70% of the combined RN and LPN total.[37] RN's are considerably

[35] As noted before, hospital labor costs consist of nurses, orderlies, administrators, and custodial staff but not 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.

[36] Because the dependent variable is mechanically related to the cross-sectional variation of Medicare share of patient days in 1983, we again drop 1980 from the sample and re-define the cross-sectional variation as Medicare share of patient days in 1980.

[37] 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.

more skilled than LPN's. RN certification requires about 2 to 4 years of training, compared to only 1 to 2 for a LPN. This is reflected in their hourly wages, with RN's earning about 50 percent more than LPN's.[38]

Table 9 shows that the introduction of PPS appears to be associated with an increase in the proportion of nurses that are relatively more skilled nurses (the RN's). These results are somewhat weaker than our previous findings; for example, in one specification, there is evidence of a marginally statistically significant effect prior to PPS in the same direction as the PPS (column 2). In our preferred specification (column 5), the pre-PPS effect is not statistically significant, but is still of the same sign as the main effect and about half the magnitude. Overall, we interpret these findings as broadly suggestive of a potential increase in the skill content of employment associated with the induced increase in technology adoption.

6.6 Alternative Interpretations

So far we have offered our preferred interpretation that the differential changes in factor demands and technology are a response to changes in relative factor prices induced by the PPS. Nevertheless, there is a number of alternative interpretations for our results, particularly for the results on the capital-labor ratio and technology adoption. In this subsection, we discuss these alternative interpretations, and why they are less compelling than our preferred interpretation.

Let us first consider the increase in the depreciation share in high-Medicare share hospitals following PPS documented in Table 2. One alternative interpretation is that because depreciation is a backward looking measure, the ratio of depreciation to operating expenses may mechanically increase in response to a proportional scaling back of capital and labor inputs. Yet this alternative explanation would also 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. In addition, this explanation is not consistent with the PPS-induced changes in technology adoption and skill composition shown in Tables 6, 7 and 9.

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 at some point be made prospective; 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 own historical costs would

[38] Hourly wage estimates by occupation are from the 2000 Merged Outgoing Rotation Groups of the CPS. We are grateful to Doug Staiger for providing us with these estimates.

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 (i.e., interest expenditures, or leveraging) rather than on the depreciation share per se. However, we find no evidence that PPS is associated with an increase in debt financing of capital expenditures ("leveraging up").[39] Finally, this type of gaming response would not be expected to translate into real effects on other margins, such as technology adoption or the skill composition of the workforce.

Turning to the technology results, our finding of a PPS effect on some technologies not directly reimbursed by Medicare may be interpreted as casting doubt on our other technology results. However, we believe that these findings are in fact quite consistent with the growing body of evidence of "spillovers" from the nature of insurance for one group of patients to the treatment of another group of patients.[40] In general, the estimated magnitudes of these "spillover" effects on adoption of non-Medicare technologies are considerably smaller than the impact of PPS on adoption of technologies used by the Medicare population (see Table 7). One way to incorporate such spillovers into the framework developed in Section 2 would be to relax the assumption that the other inputs in the production function (1), $\tilde{F}$, represented by z_i, are constant. For example, in the model of subsection 2.2, a change from full cost to partial cost reimbursement may encourage a firm to switch its managerial efforts (a component of z_i) from Medicare-related activities to non-Medicare activities. In this case, we may expect an increase in non-Medicare related technologies.[41] Another possibility is that there are complementarities in a range of new technologies, and adopting a number of new Medicare-related technologies may reduce the costs (and/or increase the benefits) of adopting other, non-Medicare, technologies. Finally, in practice, Medicare's cost-based reimbursement rules permitted hospitals

[39] Specifically, we find no evidence of an increase in the ratio of interest expenditures to depreciation expenditures (results not shown). Consistent with this, Table 12 (discussed in Section 7) shows no effect of PPS on log interest expenses.

[40] For example, Baicker and Staiger (2004) find that increases in the hospital reimbursement rate of Medicaid—which primarily reimburses for childbirth and pediatrics—is 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. Such "spillovers" could reflect a variety of factors including charitable objectives of hospitals and jointness in production.

[41] Note that this is a distinct effect on technology adoption from that highlighted in Proposition 3, which focuses on the technologies directly substituting for the tasks previously performed by the labor that was being subsidized under the full cost reimbursement regime.

considerable latitude in determining which costs to assign to Medicare (OTA, 1984, CBO, 1988). A change in the reimbursement rules for Medicare inputs is therefore likely to have also changed the effective reimbursement for some non-Medicare inputs as well. In light of all these considerations, we do not find it surprising that there is some spillover of PPS reform to non-Medicare technologies.

Another potential concern with the technology adoption results is that the time period we are examining is one of secular increases in medical technology, and the elderly are among the most intensive users of medical technology. This raises concerns that a correlation between the underlying secular increase in technology and our cross-sectional variation (hospitals' Medicare share) might spuriously suggest an impact of changes in Medicare on technology adoption. In this regard, the evidence of an impact of PPS on non-Medicare technologies offers some reassurance, as does the fact that several of the technologies for which we find an impact of PPS are in fact *not* diffusing over our sample period (see Figure 5). Most importantly, the results from our pre-specification test ($d_{1983} \cdot m_i$) also suggest that there were not systematically differential trends in technology adoption across hospitals with different Medicare share *before* the introduction of PPS. As another check, in Section 7 below, we also show results with linear time trends interacted with Medicare share, which show, in fact, a stronger effect of PPS on technology adoption, substantially alleviating the concerns that our results are driven by underlying secular trends.

Finally, an alternative interpretation for our technology findings is that, as has been noted by McClellan (1996, 1997), PPS reimbursement on the price cap (i.e., output) side is not fully prospective; the reimbursement a hospital receives for a Medicare patient varies not only based on the patient's diagnosis, but also, in some cases, on the type of treatment he or she receives, particularly the type of surgery if any.[42] These features may have increased hospitals' incentives to perform these surgeries, and relatedly to adopt the technologies needed to perform them. In practice, however, several pieces of evidence suggest that this type of incentive effect is unlikely to be the driving factor behind our technology adoption results. The most convincing evidence is that we find equally strong results for procedures which are not reimbursed more generously after PPS. For example, as noted by McClellan (1996), for ad hoc reasons, while use of CABG or PCTA procedures are associated with higher reimbursement rates for the treatment of a

[42]For example, there are separate reimbursement rates for patients who have a heart attack (AMI) but do not undergo certain intensive procedures, patients who have a heart attack but undergo a revascularization procedure known as percutaneous transluminal coronary angioplasty (PCTA), and patients who have a heard attack and undergo coronary artery bypass graft (CABG) surgery.

heart attack, the use of the cardiac care unit (CCU) is not. However, when we implement the type of hazard model analysis shown in Table 7 for adoption of the CCU, the evidence indicates 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.[43]

In addition, other evidence, from subsequent changes in the relative reimbursement rates of various health services, shows virtually no real response of hospitals in the intensity with which a patient is treated or the resources spent on the patient (Dafny, 2005). There is evidence of substantial nominal responses (termed "upcoding") in the reimbursement group in which the patient is placed in response to changes in the relative reimbursement rates of various health services; these "upcoding" responses are substantially greater among for-profit hospitals (Dafny, 2005, Silverman and Skinner, 2004). In contrast, our findings suggest that the increase in depreciation share, the decrease in labor costs, and the lack of an effect on depreciation costs associated with PPS were quite similar in publicly-owned, for-profit, and non-profit hospitals, and that the technology adoption effects of PPS were in fact somewhat more pronounced in publicly-owned hospitals than in for-profit or non-profit hospitals (results not shown).[44]

7 Robustness Checks

7.1 Alternative Specifications

We present robustness results for our main dependent variables: capital-labor ratio (depreciation share), log labor inputs (log operating expenses), log capital inputs (log depreciation expenses), and the number of facilities.[45] In line with the pattern of results shown in Tables 2, 3, 4 and 6, for the first three outcomes, we report results with the post-PPS period parameterized by a linear trend as in equation (28), while for the number of facilities we report results

[43] Information on whether a hospital has a CCU is available from 1980-1985 (see Appendix Table A). The data indcate a slight decline in the probability that a hospital has a CCU between 1980 (70%) and 1985 (67%). The other technology adoption results in Table 7 are robust to excluding 1986 from the data.

[44] Our findings of broadly similar responsiveness to PPS across hospitals of differnet ownership types is consistent with a large empirical literature that has tended to find little differences in hospital behavior by ownership type (see, e.g., Sloan, 2002, for a recent review). Indeed, Silverman and Skinner (2004) observe that "upcoding" is something of an anomoly in that it appears to be the one form of hospital behavior that is substantially different by ownership type.

[45] To save space, we only report the robustness analysis of the number of facilities in the OLS specification. Results from the conditional fixed effect Poisson model were similar, except that we did not estimate the first-differenced specification (column 4) since this specification can not be consistently estimated within the conditional fixed effects Poisson model.

with the post-PPS period parameterized by a single indicator post-PPS dummy variable as in equation (26).

Column (1) of Table 10 reproduces the baseline results. As discussed previously, the general finding is one of no or insignificant pre-PPS differences by Medicare share, combined with a significant post-PPS effect on three of the four outcomes (all but log capital inputs). The only exception is in Panel B for log labor inputs, where there is a marginally significant pre-PPS effect of the opposite sign of the estimated PPS effect.

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 generally robust to the inclusion of this linear trend.[46]

A related but different concern is that of mean reversion. In particular, if high Medicare share hospitals are adjusting back to some hospital-specific equilibrium level, this may be picked up by our post-PPS times Medicare share interaction. To investigate this potential issue, column (3) presents a very flexible (and demanding) specification, in which we interact the value of the dependent variable for each hospital in 1982 with a full set of year dummies. This specification thus controls flexibly for potential mean reverting patterns. The estimates are remarkably similar to the baseline case and show no evidence that mean reversion 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, p. 284), and on the potential importance of measurement error in the data (Griliches and Hausman, 1986). The first-differenced results in column (4) are very similar to the baseline results; the one exception is the results for number of facilities (Panel D), which now show a pre-PPS effect of the same sign as the estimated PPS effect that is significant at 5%. However, since this is the only specification among many where

[46] The only exception is in Panel C for log capital inputs, where we now find a significant pre-PPS effect. We find a similar significant pre-PPS positive effect on log capital inputs in the first-differenced specification in column (4) and the specification excluding small regional hospitals in column (7) as well. Nevertheless, since neither here nor in our base specifications is there any evidence of an impact of PPS on total log capital inputs, these results are not a major problem for our approach and simply show that the capital input results are in general less precisely estimated.

we find a same-signed significant pre-PPS effect for number of facilities, we interpret this as partly driven by sampling variability.

Another way of directly dealing with concerns about measurement error in our key variable, the Medicare share, is to instrument for the 1983 Medicare share with past values. This exercise is performed in column (5), and once again the results are very similar to the baseline estimates. The only exception is in Panel C where now there is a small and marginally significant negative effect on log capital inputs. Since the baseline estimate in column (1) is also negative (but insignificant) for this variable, this evidence might suggest that there might have been a small decline in log capital inputs following the introduction of PPS, although this result is not robust across specifications (see especially column 8). Whether or not this is the case is not essential for the interpretation of the rest of our results.

Several other specification checks investigated the sensitivity of our findings to differences across areas and groups of hospitals. Since the price cap of Medicare PPS was phased in over a four-year period as a combination of hospital-specific historical rates, regional average rates and national rates (CBO, 1998, Gaumer and Staiger, 1990), regional differences in the level of the price cap might contribute to differential regional effects of PPS. Column (6) includes a full set of interactions between the (nine) census region dummies and year effects. In addition, exceptions to PPS for some small rural hospitals made the reimbursement of operating costs potentially not as prospective for these hospitals, which constitute about 20 percent of all hospitals, although obviously a much smaller proportion of hospital beds (Staiger and Gaumer, 1990, Newhouse, 2002, p. 31). Column (7) therefore excludes approximately 20 percent of hospitals that are outside an MSA and had fewer than 50 beds in 1983. The results in column (6) and (7) are again very similar to the baseline estimates in column (1), with the only exception that we now find a statistically significant opposite-signed pre-PPS effect for the number of facilities (Panel D), and a statistically significant positive pre-PPS effect on capital inputs (Panel C) in column (7).

We also looked at results weighted by hospital size (measured as the number of beds in 1983). Hospital size is extremely right skewed; while the 90th percentile is only four times bigger than the median, the 99th percentile is more than double the 90th percentile (and the largest hospitals are over twice as big as the 99th percentile). Consequently, a regression weighted by hospital size effectively only compares the behavior of the hospitals within the top 5th percentile or so. To avoid this, while still weighting by hospital size, we exclude the top ventile (i.e., the top 5%) of hospitals.[47] These weighted results are shown in column (8). The results are on the whole similar to those in column (1), with the only difference that we now find a statistically significant opposite-signed pre-PPS effect for the number of facilities (Panel D), and there is a positive effect on log capital inputs (Panel C).

Another dimension of potential heterogeneity in hospitals' response to PPS concerns whether or not they are vertically integrated with non-hospital organizations—such as rehabilitation centers or nursing homes—which were exempted from the PPS reform and continued to be reimbursed on a cost-plus basis. Hospitals that are vertically integrated with these exempted units might find it easier to move various forms of care to the parts of the hospital that are exempted from PPS. To investigate this, we reestimated our models limiting the sample to the approximately 85 percent of hospitals that are not vertically integrated with nursing homes. The estimates in column (9) are virtually identical to the baseline results and suggest that our results are not driven by relabelling of care within a hospital.

Given the evidence in Table 7 of an impact of PPS on the adoption of non-Medicare technologies such as the neo-natal intensive care unit (NICU), one concern may be that our results are capturing differential trends across hospitals related to other demographic characteristics of their patient-bases. To check for this possibility, in column (10) we include additional controls for $d_{1983} \cdot b_i$ and $POSTTREND_t \cdot b_i$, where b_i is the new born share of non-Medicare patient days (defined analogously to m_i). The inclusion of these variables has no major effect on any of our results. In addition, the coefficients on $d_{1983} \cdot b_i$ and $POSTTREND_t \cdot b_i$ are economically and statistically insignificant (not shown in Table 10), except in the case of the hazard model adoption of the NICU, where they have the expected sign, but their magnitude is much smaller than those of the changes in response to relative factor prices induced by PPS.

Finally, we explored potential heterogeneity in the estimated effect of PPS based on the type of variation in m_i used to identify its effects. As discussed, federally-owned hospitals, long-term hospitals, and certain speciality hospitals—together totalling 15 percent of all hospitals—were exempted from PPS. Recall that we coded these hospitals as having a zero Medicare share (see Figure 4). Table 11 explores 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. Column (1) replicates the baseline findings. In column (2) (labeled "using only within variation"), we add a full set of year dummies interacted with each of the three

[47] Excluding the top or the bottom ventile or the top or the bottom decile of hospitals from the unweighted regressions has no perceptible effect on the results (not shown). Moreover, regressions weighted by log of hospital size without excluding the top 5% also produce very similar results (again not shown to save space).

categories that provide an exemption from PPS to equations (26) and (28). 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 (3) (labeled "using only between variation") 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 $POSTTREND_t \cdot m_i$ 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. Most of the estimated effects of quite similar in size using either source of variation, though the estimated impact of PPS on the capital-labor ratio is substantially larger with the between variation than the within variation.

In summary, a wide variety of alternative specifications (some of them reported in Tables 10 and 11) suggest that the PPS-related increase in capital-labor ratio and decline in log labor inputs are very robust findings. The results on the number of facilities are also robust; although several specifications produced opposite-signed and statistically significant pre-PPS results which might raise concerns about mean reversion, the estimated effects on facilities are highly robust to a number of specification that control for mean reversion. The results on log capital inputs are on the whole less precise, but they are consistent with our interpretation of no effect of PPS on capital inputs.

7.2 Alternative Dependent Variables

Table 12 investigates the robustness of our results to alternative measures of various dependent variables. Once again, the first column repeats the baseline regressions for comparison. Panel A shows that the results for log labor inputs are robust to using alternative measures of labor inputs, such as log payroll expenditures rather than log operating expenditures (see column 2). Log payroll expenditures are a more direct measure of labor costs, but they are not our preferred measure, since they do not include the full set of costs that experienced the relative price change under PPS. Column (3) shows that the results are also quite similar when we use the complement—log of non-payroll operating expenses—as the dependent variable. Columns 3 and 4 show that our results for log labor inputs are also generally robust to using log employment or using log nurses, defined as RN's plus LPN's, though with both of these dependent variables, there is some evidence of pre-PPS effects, in one case of the same sign as the main effect, and in the other of the opposite sign.

Panels B and C show that the results for log capital inputs and the capital-labor ratio are robust to using interest expenses as well as (or instead of) depreciation expenses to measure capital inputs. In particular, in all cases, the PPS effect is qualitatively similar, though in some specifications there is evidence of an opposite-signed pre-PPS effect. The results in Panel B suggest that PPS is not associated with any substantive or statistical change in either log depreciation or log interest expenditures. Consistent with this, the results in Panel C suggest that the (proportional) increase in the capital-labor ratio is quite similar when depreciation expenses or interest expenses are used to proxy for capital inputs.

8 Conclusions

This paper has investigated the impact of regulation and regulatory change on firm input mix and technology choices. We presented a simple neoclassical framework that emphasizes changes in relative factor prices faced by regulated firms under different regimes and how this may affect input mix and technology choices. We then investigated this possibility empirically by studying the impact of the introduction of the Medicare Prospective Payment System (PPS) 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.

Consistent with the framework we developed, the 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. Within our theoretical framework, this would be the case 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 the question 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 encouraging capital deepening and technology adoption. This is an interesting question for future research.

Our findings regarding technology adoption run counter to the general expectation that

PPS would, if anything, 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 relative factor price changes induced by the partial cost reimbursement regime. This highlights the potential importance of the details of regulation policy in determining its ultimate impact. Interestingly, after the period of our study, there was a 10-year period during which PPS was gradually moved to a full price cap system. Proposition 5 in Section 2 shows that this move from partial cost reimbursement to full price cap should be associated with a decline in the capital-labor ratio, and may also retard technology adoption. An empirical investigation of the impact of the move to the full price cap system is another interesting area for future research.

Naturally, our empirical results only speak to the impact of regulatory change in the health care sector. It is possible that the health care sector is not representative of regulatory effects in other sectors, for example because most hospitals are non-profit or public entities. Nevertheless, the theoretical framework we develop should be applicable to other regulated industries, many of which operate under some form of partial cost reimbursement (see Joskow, 2005). An investigation of the response of input and technology choices to similar regulatory changes in other industries is another obvious area for future research and would be particularly useful for understanding the extent to which the results presented here generalize to other industries.

9 Appendix A: Proofs from Section 2

Proof of Proposition 1: (11) follows immediately by comparing (10) to (6). In addition, taking the ratio of (10) to (6), we obtain

$$\frac{F_K\left(A_i, L_i^p, K_i^p\right)/F_L\left(A_i, L_i^p, K_i^p\right)}{F_K\left(A_i, L_i^f, K_i^f\right)/F_L\left(A_i, L_i^f, K_i^f\right)} = \left(1 - m_i s_L\right).$$

When $F\left(A_i, L_i, K_i\right)$ is homothetic in L_i and K_i, the left-hand side is simply a (decreasing) function of $\left(K_i^p/L_i^p\right)/\left(K_i^f/L_i^f\right)$, which immediately establishes (12). **QED**

Proof of Proposition ??: Given $\left(1+\theta m_i\right)/\left(1-m_i s_L\right) \geq 1$, comparison of (4) and (5) to (8) and (9) immediately implies that $F_K\left(A_i, L_i^p, K_i^p\right) < F_K\left(A_i, L_i^f, K_i^f\right)$ and $F_L\left(A_i, L_i^p, K_i^p\right) \leq F_L\left(A_i, L_i^f, K_i^f\right)$. Since F exhibits decreasing returns, this is not possible with $K_i^p \leq K_i^f$ and $L_i^p \leq L_i^f$, proving the first part of the proposition. Next, from Proposition 1, $K_i^p \leq K_i^f$ and $L_i^p > L_i^f$ is not possible. So to obtain a contradiction suppose that $K_i^p > K_i^f$ or $L_i^p \leq L_i^f$. But given $F_{LK} > 0$ and $F_{LL} < 0$, this implies $F_L\left(A_i, L_i^p, K_i^p\right) > F_L\left(A_i, L_i^f, K_i^f\right)$, which contradicts the above inequalities, so $K_i^p > K_i^f$ or $L_i^p \leq L_i^f$ is not possible. This proves that we must $K_i^p > K_i^f$ and $L_i^p > L_i^f$ as claimed in the second part of the proposition. **QED**

Proof of Proposition 2: To prove this proposition, totally differentiate the first-order conditions (4) and (5) with respect to L_i, K_i and s_L, and write the resulting system as

$$\begin{pmatrix} F_{LL} & F_{LK} \\ F_{LK} & F_{KK} \end{pmatrix} \begin{pmatrix} dL \\ dK \end{pmatrix} = \begin{pmatrix} -m_i \\ 0 \end{pmatrix} ds_L.$$

Applying Cramer's rule immediately gives (13), and the fact that $F_{LL}F_{KK} - \left(F_{LK}\right)^2 > 0$ and $F_{KK} < 0$ follows from the concavity of F, thus establishing the fact that $dL_i\left(s_L\right)/ds_L > 0$ as stated in (13). Similarly, from Cramer's rule

$$\frac{dK_i\left(s_L\right)}{ds_L} = \frac{m_i F_{LK}}{F_{LL}F_{KK} - \left(F_{LK}\right)^2}. \tag{32}$$

Therefore, this will be positive when $F_{LK} > 0$ and negative when $F_{LK} < 0$. When F is homogeneous of degree α, i.e., $F\left(A_i, L_i, K_i\right) = H_1\left(A_i\right)\phi\left(L_i, K_i\right)^\alpha$, it is easy to verify that

$$F_{LK} \propto \left(\alpha - 1\right)\phi_L\phi_K + \phi_{LK}\phi.$$

Recalling that when ϕ exhibits constant returns to scale, the elasticity of substitution is given by

$$\sigma_\phi \equiv \frac{\phi_L\phi_K}{\phi_{LK}\phi},$$

which immediately implies that $F_{LK} < 0$ if and only if $1/\left(1-\alpha\right) < \sigma_\phi$ and positive if and only if $1/\left(1-\alpha\right) > \sigma_\phi$, thus establishing (14). **QED**

Proof of Proposition 3: Using the form in (16), the first-order necessary and sufficient conditions (under full cost reimbursement) are

$$\begin{aligned} q\beta\psi_L(A_i, L_i)\psi(A_i, L_i)^{\beta-1}H_s\left(K_{s,i}\right) &= \left(1 - m_i s_L\right)w \\ q\beta\psi_A(A_i, L_i)\psi(A_i, L_i)^{\beta-1}H_s\left(K_{s,i}\right) &= \left(1 - m_i s_K\right)R\kappa_i\left(A_i\right) \\ q\psi(A_i, L_i)^{\beta}H_s'\left(K_{s,i}\right) &= \left(1 - m_i s_K\right)R. \end{aligned}$$

Taking logs and totally differentiating with respect to A_i, L_i, $K_{s,i}$ and s_L, we obtain the system of equations

$$\begin{pmatrix} \frac{\psi_{LL}(A_i,L_i)}{\psi_L(A_i,L_i)} - (1-\beta)\frac{\psi_L(A_i,L_i)}{\psi(A_i,L_i)} & \frac{\psi_{AL}(A_i,L_i)}{\psi_L(A_i,L_i)} - (1-\beta)\frac{\psi_A(A_i,L_i)}{\psi(A_i,L_i)} & \frac{\eta}{K_{s,i}} \\ \frac{\psi_{AL}(A_i,L_i)}{\psi_A(A_i,L_i)} - (1-\beta)\frac{\psi_L(A_i,L_i)}{\psi(A_i,L_i)} & -\frac{\kappa_i'(A_i)}{\kappa_i(A_i)}\frac{\psi_{AA}(A_i,L_i)}{\psi_A(A_i,L_i)} - (1-\beta)\frac{\psi_A(A_i,L_i)}{\psi(A_i,L_i)} & \frac{\eta}{K_{s,i}} \\ \beta\frac{\psi_L(A_i,L_i)}{\psi(A_i,L_i)} & \beta\frac{\psi_A(A_i,L_i)}{\psi(A_i,L_i)} & \frac{\eta-1}{K_{s,i}} \end{pmatrix} \begin{pmatrix} dL_i \\ dA_i \\ dK_{s,i} \end{pmatrix} = \begin{pmatrix} \frac{-m_i}{1-m_i s_L} \\ 0 \\ 0 \end{pmatrix} ds_L.$$

Applying Cramer's rule again, and using the fact that (16) is strictly concave, we immediately obtain $dL_i(s_L)/ds_L > 0$, $dK_{s,i}(s_L)/ds_L > 0$ and that $dA_i(s_L)/ds_L$ is proportional to

$$(1-\eta)\psi_{AL}\psi + (1-\beta)(\eta-1)\psi_A\psi_L + \beta\eta\psi_A\psi_L.$$

Again using the definition of the elasticity of substitution with constant returns to scale, i.e., $\varepsilon_\psi \equiv \psi_A\psi_L/\psi_{AL}\psi$, and the fact that $K_{a,i}$ is a monotonic transformation of A_i yields (18). **QED**

Proof of Proposition 6: The first order conditions now imply

$$\frac{F_K\left(A_i, L_i^p, K_i^p\right)/F_L\left(A_i, L_i^p, K_i^p\right)}{F_K\left(A_i, L_i^f, K_i^f\right)/F_L\left(A_i, L_i^f, K_i^f\right)} = \frac{\left(1-m_i^f s_L\right)\left(1-m_i^p s_K\right)}{\left(1-m_i^f s_K\right)}.$$

The right hand side of this equation being less than 1 is sufficient for (24), which is in turn guaranteed by assumption (23). **QED**

10 Appendix B: Cost Plus Reimbursement Without Fungibility

The analysis in the text was simplified by the fact that we allowed the hospital to substitute labor (and capital) between the Medicare and non-Medicare products, and focused on the case where $s_L m_i < 1$ and $s_K m_i < 1$. The combination of these two assumptions implied that that the hospital always faced positive marginal costs of hiring more labor, capital and technology.

An alternative model would be one in which there is *cost plus* reimbursement, in the sense that for every dollar spent on capital or labor, the hospital receives more than one dollar back, that is, $s_L > 1$ and $s_K > 1$, and there is no *fungibility*. In this case, the model developed in 2.1 needs to be modified, since it would imply that the hospital would like to choose infinite amounts of capital and labor (unless F_L and F_K become negative). This would not only be unrealistic, but would also run into regulatory constraints. This Appendix briefly discusses how the analysis is modified once these regulatory constraints are incorporated. In particular, Medicare stipulates that hospitals can charge for "reasonable and customary" costs for Medicare services. We interpret this as implying that the amount of reimbursement required by the hospitals has to be less than a fraction of the average productivity of each factor that is being reimbursed under Medicare.

Let us simply focus on the Medicare services provided by the hospital and ignore technology choices (which, as before, can be incorporated in a straightforward manner). Moreover, assume throughout that $s_L > 1$ and $s_K > 1$. This implies that the profits of the hospital i are

$$\pi^f(i) = qF(L_i, K_i) + s_L w\tilde{L}_i + s_K R\tilde{K}_i - wL_i - RK_i \tag{33}$$

where L_i and K_i are the total amounts of capital and labor hired by the hospital, while $\tilde{L}_i$ and $\tilde{K}_i$ are the total amounts of labor and capital for which the hospital requests reimbursement from Medicare.

Although we have assumed that there is no fungibility, in the sense that the hospital cannot demand reimbursement for labor and capital used for other purposes, it can always use additional labor and capital for Medicare-related activities even if it does not ask for reimbursement. We will see that this might be useful depending on how tight the reimbursement constraints imposed by Medicare are.

In particular, we model these constraints as follows:

$$s_L w \tilde{L}_i \leq B_L F\left(L_i, K_i\right) \tag{34}$$

$$s_K R \tilde{K}_i \leq B_K F\left(L_i, K_i\right). \tag{35}$$

Simply put, these constraints require the reimbursement received from Medicare for labor and capital not to exceed a certain fraction of the health services provided to Medicare patients. To clarify this interpretation, for example, (34) can be expressed as $s_L w / B_L \leq F\left(L_i, K_i\right) / \tilde{L}_i$, which shows that this constraint equivalently requires the average product of labor (used for reimbursement) not to exceed a certain threshold.

All the other assumptions from the main model, in particular, that F is increasing, strictly concave and twice continuously differentiable in both of its arguments, still apply. The constraints (34) and (35) also explain why we had to allow for the hospital to be able to choose more labor and capital than the amounts for which it demands reimbursement from Medicare. In particular, imagine that B_L is very small (in the limit, $B_L \to 0$). If we had imposed that $\tilde{L}_i = L_i$ and labor were an essential factor of production, then the hospital would have to shutdown; but with our formulation, and in reality, it can function profitably by choosing $\tilde{L}_i < L_i$. This discussion also shows that if the reimbursement constraints (34) and (35) are not too binding, the solution will typically have $\tilde{L}_i = L_i$ and $\tilde{K}_i = K_i$.

Consequently, under full cost (plus) reimbursement, the firm chooses $\tilde{L}_i, L_i, \tilde{K}_i$ and K_i to maximize (33) subject to (34), (35) and the natural constraints arising from non-fungibility that $\tilde{L}_i \leq L_i$ and $\tilde{K}_i \leq K_i$ (so that the amount of labor and capital reimbursed are less than the total amount of labor and capital used in Medicare-related activities).

Lemma 1 *Profit maximization implies that with full cost reimbursement, both (34) and (35) will be binding.*

Proof. Suppose not, and that for example, (34) is slack. Since F is increasing in L_i and $s_L > 1$, the hospital can set $\tilde{L}_i = L_i$ and increase L_i until (34) binds, which will increase the value of profits in (33), yielding a contradiction. The same argument applies to (35), proving the lemma. ■

This lemma enables us to substitute for constraints (34) and (35) and write the maximization problem under full cost reimbursement regulation as follows:

$$\max_{\tilde{L}_i, L_i, \tilde{K}_i, K_i} \left(q + B_L + B_K\right) F\left(L_i, K_i\right) - wL_i - RK_i \tag{36}$$

subject to $\tilde{L}_i \leq L_i$ and $\tilde{K}_i \leq K_i$. Intuitively, if the hospital will hire more labor or capital than what it demands reimbursement for, the marginal cost of this labor and capital will be given by the factor market prices, w and R, and the amounts $B_L F\left(L_i, K_i\right)$ and $B_K F\left(L_i, K_i\right)$ will be perceived by the hospital as lump-sum transfers. Alternatively, the firm will hire exactly $\tilde{L}_i$ and $\tilde{K}_i$.

The first-order conditions of this problem are

$$\left(q + B_L + B_K\right) F_L\left(L_i^f, K_i^f\right) \geq w \text{ and } \tilde{L}_i^f \leq L_i^f \tag{37}$$

$$\left(q + B_L + B_K\right) F_K\left(L_i^f, K_i^f\right) \geq R \text{ and } \tilde{K}_i^f \leq K_i^f, \tag{38}$$

both holding with complementary slackness and f denoting full cost reimbursement.

Lemma 1 has another important implication for our analysis. If the solution to the maximization problem of the hospital involves $\tilde{L}_i^f = L_i^f$ and $\tilde{K}_i^f = K_i^f$, then (34) and (35) define two equations in two unknowns $\tilde{L}_i^f$ and $\tilde{K}_i^f$, and moreover, decreasing returns to capital and labor implies that there exists a unique tuple (L^*, K^*) satisfying these two equations. Therefore, if we have the second inequalities in (37) and (38) hold as equality, we must have $\tilde{L}_i^f = L_i^f = L^*$ and $\tilde{K}_i^f = K_i^f = K^*$. The above discussion then suggests that as long as (34) and (35) are not very restrictive (i.e., are sufficiently generous), we will be in a situation in which the firm hires the levels of labor and capital that will exactly satisfy these two constraints, (L^*, K^*).

Next let us turn to the partial cost reimbursement regime, where there is no reimbursement for labor, so the constraint (34), as well as s_L, are removed, and the firm now receives $q + B_P$ per unit of Medicare health services where $B_P \geq 0$. The maximization problem then becomes

$$\pi^f(i) = (q + B_P) F(L_i, K_i) + s_K R \tilde{K}_i - wL_i - RK_i \tag{39}$$

subject to (35) and $\tilde{K}_i \leq K_i$. We then immediately have the following result which parallels Lemma 1 (proof omitted):

Lemma 2 *Profit maximization implies that with partial cost reimbursement, (35) will be binding.*

Consequently, the maximization problem of the firm can be written as:

$$\max_{\tilde{L}_i, L_i, \tilde{K}_i, K_i} (q + B_P + B_K) F(L_i, K_i) - wL_i - RK_i,$$

subject to $\tilde{K}_i \leq K_i$. In this case, we have the following first-order conditions:

$$(q + B_P + B_K) F_L(L_i^p, K_i^p) = w, \text{ and}$$

$$(q + B_P + B_K) F_K(L_i^p, K_i^p) \geq R \text{ and } \tilde{K}_i^p \leq K_i^p,$$

with the second condition holding with complementary slackness.

The difficulty in the analysis in this case stems from the fact that either of (34) or (35) could be very tight, with correspondingly large Lagrange multipliers. For example, this would be the case when $B_L \to 0$, so that there was effectively no reimbursement of labor because of the tightness of the "reasonable and customary" constraint. Nevertheless, the following proposition can be established:

Proposition 7 *Suppose that under full cost reimbursement $L_i^f = L^*$ and $K_i^f = K^*$. Consider a change to partial cost reimbursement with $B_P < B_L$, then we have*

$$L_i^p < L_i^f. \tag{40}$$

Moreover, if F is homogeneous of degree $\beta < 1$ in L_i and K_i, then

$$\frac{K_i^f}{L_i^f} < \frac{K_i^p}{L_i^p}. \tag{41}$$

Proof. The first-order conditions for (36) imply that $(q + B_L + B_K) F_L(L^*, K^*) \geq w$ and $(q + B_L + B_K) F_K(L^*, K^*) \geq R$, while the first-order conditions for (39) imply $(q + B_P + B_K) F_L(L_i^p, K_i^p) = w$ and $(q + B_P + B_K) F_K(L_i^p, K_i^p) \geq R$. To obtain a contradiction suppose that $L_i^p \geq L_i^f$. Lemma 2 implies that (35) holds as equality. Since $L_i^p \geq L_i^f = L^*$, (35) then implies $K_i^p \geq K_i^f = K^*$. First, suppose that $K_i^p = K^*$. Then diminishing returns to labor implies that $(q + B_L + B_K) F_L(L^*, K^*) \geq w$ is inconsistent with $(q + B_P + B_K) F_L(L_i^p, K^*) = w$, $L_i^p \geq L^*$ and $B_P < B_L$, yielding a contradiction.

Second, suppose that $K_i^p > K^*$. Then (38) implies $(q + B_P + B_K) F_K (L_i^p, K_i^p) = R$. Then, $B_P < B_L$ implies that

$$\begin{aligned} (q + B_P + B_K) F_L (L_i^p, K_i^p) &> (q + B_L + B_K) F_L (L^*, K^*) \\ (q + B_P + B_K) F_K (L_i^p, K_i^p) &> (q + B_L + B_K) F_K (L^*, K^*), \end{aligned}$$

which is inconsistent with $K_i^p > K^*$ and $L_i^p \geq L^*$ given decreasing returns, yielding another contradiction, and establishing that we must have $L_i^p < L^*$, i.e., (40).

To obtain (41), first note that if $K_i^p \geq \tilde{K}_i^f = K^*$, given (40), (41) would apply immediately. Therefore, we only have to show that it also holds when $K_i^p < \tilde{K}_i^f = K^*$. Suppose this is the case. Then, use Lemma 2 and the homogeneity assumption on F, to reexpress (35) as

$$s_K R \tilde{K}_i^p (K_i^p)^\beta \leq B_K F \left(\frac{L_i^p}{K_i^p}, 1 \right).$$

Since $\tilde{K}_i^p \leq K_i^p < \tilde{K}_i^f = K^*$, it must be that $L_i^p / K_i^p < L_i^f / K_i^f$, establishing (41). ■

This proposition generalizes the results from our basic analysis with fungibility in subsection 2.1 to the case without fungibility, though the results are weaker since they hold under some additional conditions. Most importantly, the main results apply as long as the full cost reimbursement is sufficiently generous to start with so as to ensure $L_i^f = \tilde{L}_i^f = L^*$ and $K_i^f = \tilde{K}_i^f = K^*$, and partial cost reimbursement is less generous than full cost reimbursement as captured by the condition that $B_P < B_L$. Both of these appear as plausible conditions in the context of the PPS reform.

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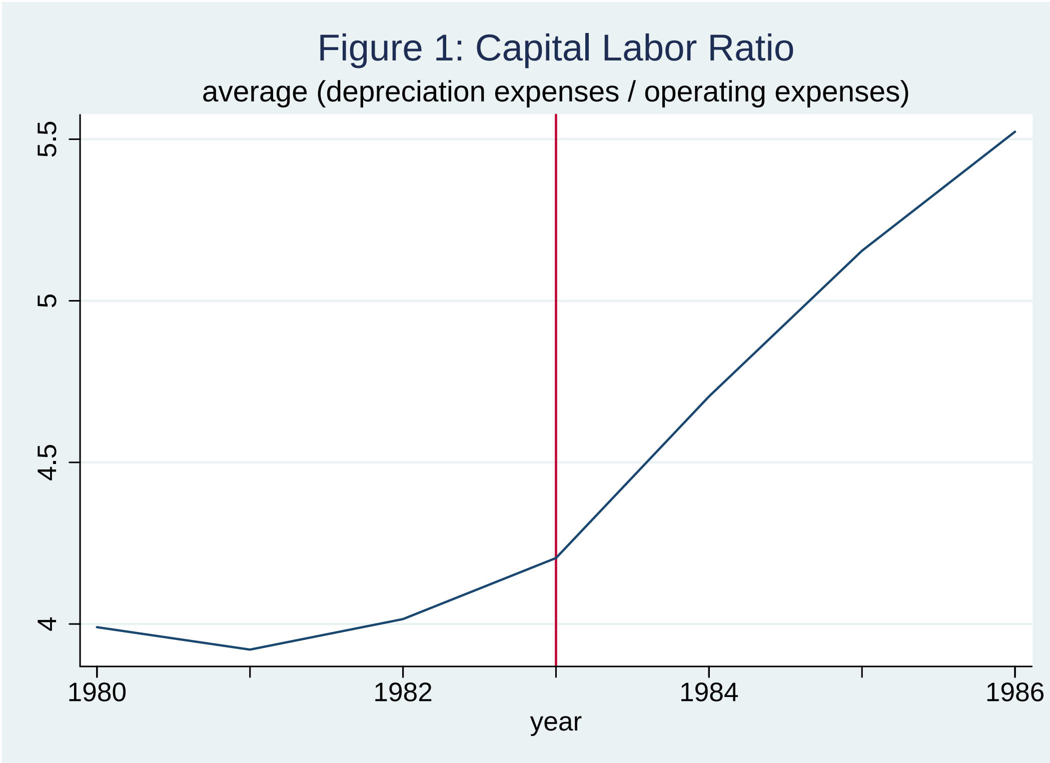

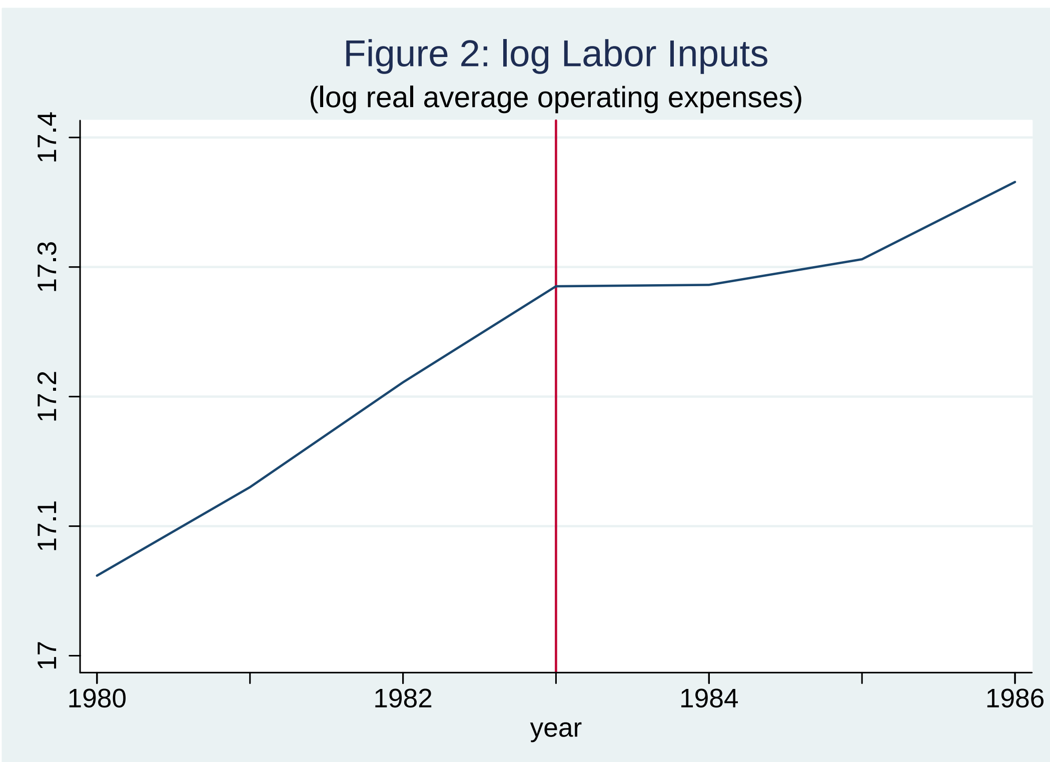

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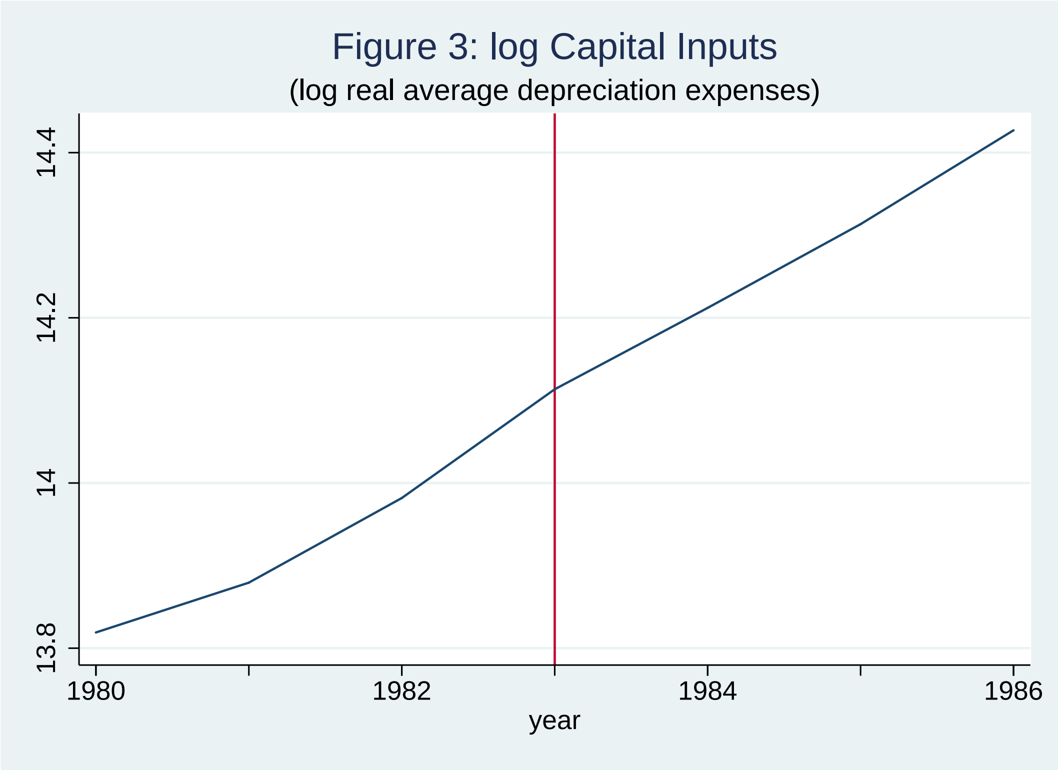


Figure 3: log Capital Inputs

Dollar amounts are measured in 2004 dollars.

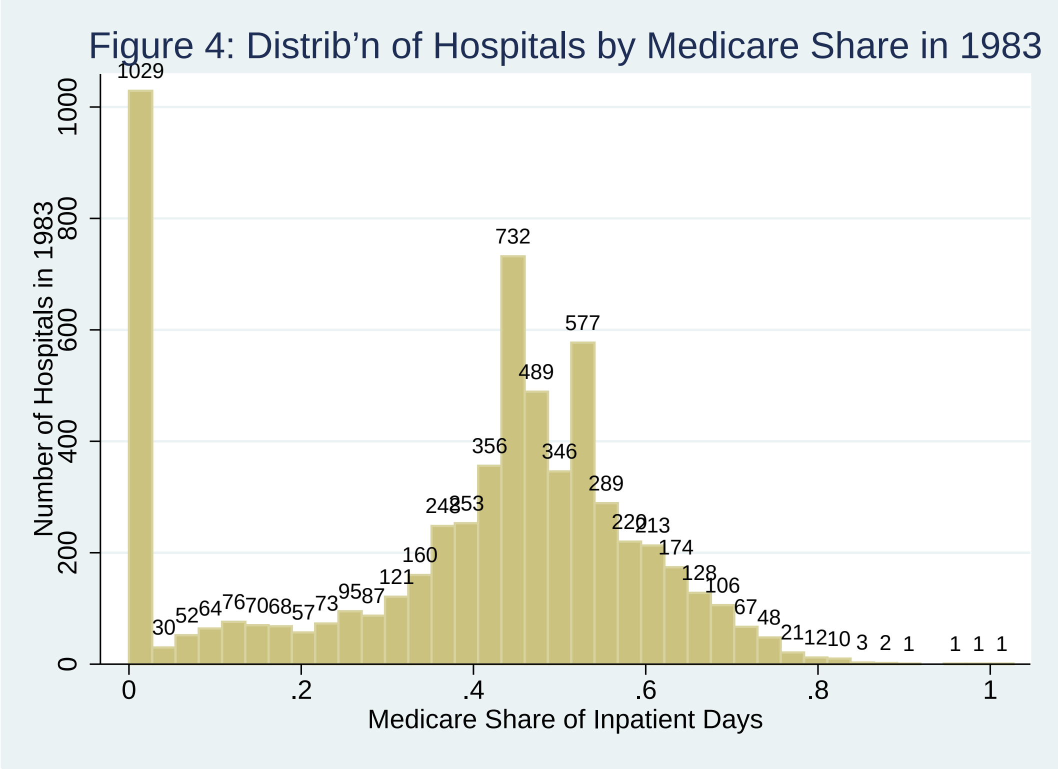
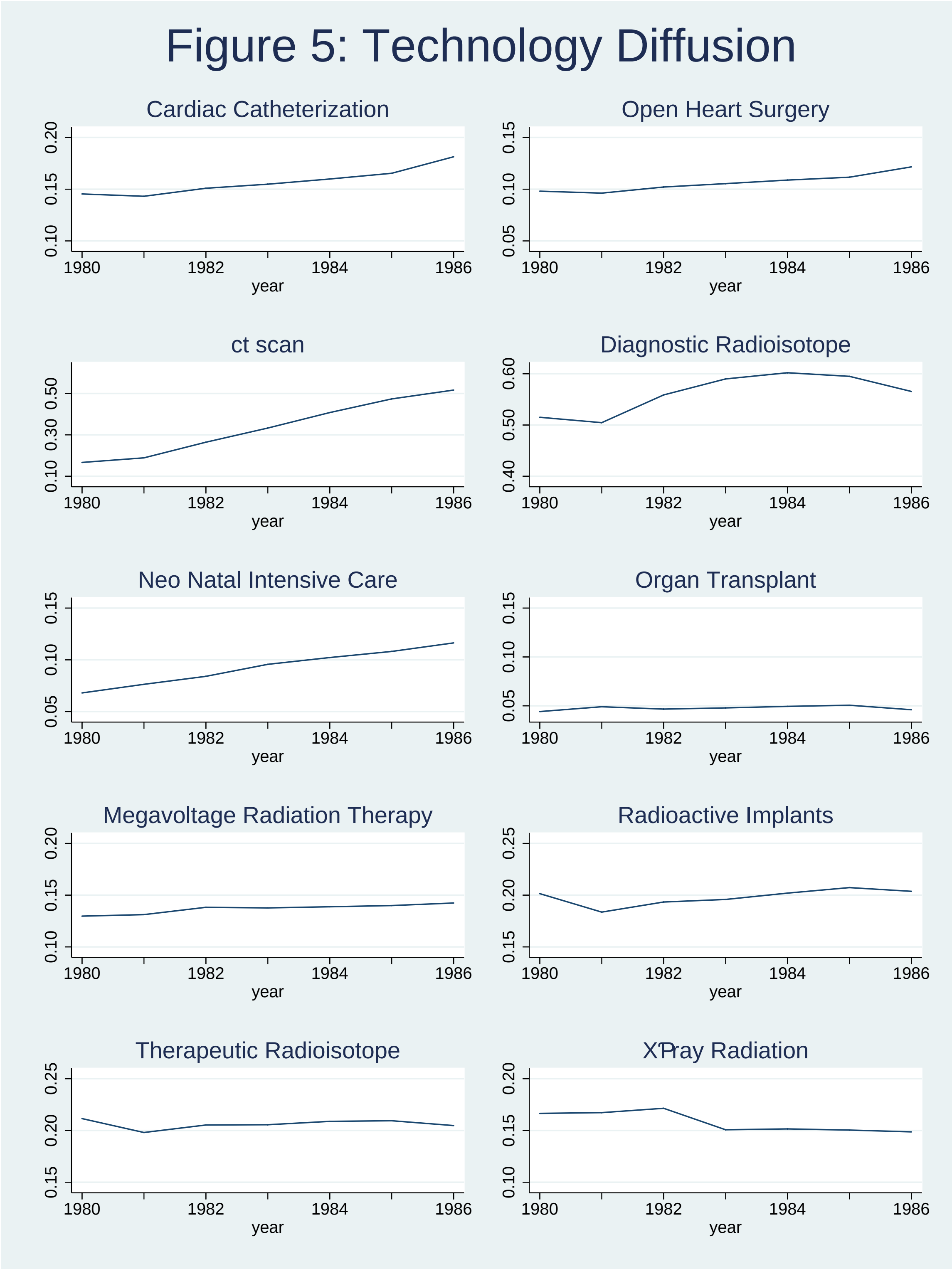


Figure 4: Distrib'n of Hospitals by Medicare Share in 1983



Note: Figures show percent of hospitals with given technology in each year.

Table 1: Summary Statistics

Variable	Average	Standard Deviation
Medicare Share of Inpatient Days in 1983	0.38	0.21
Real Operating Expenditures ('000)	$31,300	$44,500
Real Capital Expenditures (Interest plus Depreciation) ('000)	$2,156	$3,459
Real Depreciation Expenditures ('000)	$1,379	$2,224
Capital Share (Capital / Operating)	7.09%	4.90%
Depreciation Share (Depreciation / Operating)	4.50%	2.50%
Skill Ratio (Registered Nurses / Registered Nurses + Licensed Nurse Practitioners)	70%	16%
Proportion Short Term	93.6%	
Proportion General	86.8%	
Proportion Proprietary	14.5%	
Proportion Non-Profit	49.0%	
Proportion Public, Non-Federal	31.5%	
Proportion Federal	5.0%	

Note: Table reports averages for the various hospital characteristics. All dollar estimates are in thousands of 2004 dollars. N = 43,188, except for skill composition where N = 43,162. Data consist of a total of 6,280 hospitals, of which 5,881 (94 percent) are in the data for all seven years, and all are in the data for at least two years. All hospitals in the sample have information on Medicare share in 1983.

Table 2: The Impact of PPS on the Capital-Labor Ratio

	(1)	(2)	(3)	(4)	(5)
POST*m_i	1.129	1.122			
	(0.108)	(0.121)			
POSTTREND*m_i				0.538	0.532
				(0.050)	(0.053)
d_{81}*m_i			0.153		
			(0.114)		
d_{82}*m_i			-0.388		
			(0.131)		
d_{83}*m_i		-0.028	-0.109		-0.060
		(0.098)	(0.136)		(0.088)
d_{84}*m_i			0.601		
			(0.163)		
d_{85}*m_i			1.068		
			(0.172)		
d_{86}*m_i			1.474		
			(0.189)		

Notes: Dependent variable is depreciation share. Table reports results from estimating equations (35) - (38) by OLS. All regressions include hospital and year fixed effects. Mean dependent variable is 4.5. POST is an indicator variable for the years 1984 – 1986. POSTTREND is 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986 respectively. d_t is an indicator variable for year *t*. 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. N = 43,188. In column (3), omitted category is d_{80}*m_i. To interpret the magnitudes, recall that the average Medicare share in 1983 is about two-fifths.

Table 3 The Impact of PPS on Log Labor Inputs

	(1)	(2)	(3)	(4)	(5)
POST* m_i	-0.141	-0.135			
	(0.016)	(0.018)			
POSTTREND* m_i				-0.070	-0.068
				(0.007)	(0.008)
d_{81}* m_i			0.003		
			(0.016)		
d_{82}* m_i			0.034		
			(0.020)		
d_{83}* m_i		0.021	0.034		0.022
		(0.015)	(0.021)		(0.013)
d_{84}* m_i			-0.052		
			(0.023)		
d_{85}* m_i			-0.138		
			(0.025)		
d_{86}* m_i			-0.184		
			(0.026)		

Notes: Dependent variable is log operating expenditures. Table reports results from estimating equations (35)- (38) by OLS. All regressions hospital and year fixed effects. POST is an indicator variable for the years 1984 – 1986. POSTTREND is 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986 respectively. d_t is an indicator variable for year *t*. 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. N = 43,188. In column (3), omitted category is d_{80}* m_i. To interpret the magnitudes, recall that the average Medicare share in 1983 is about two-fifths.

Table 4 The Impact of PPS on Log Capital Expenditures

	(1)	(2)	(3)	(4)	(5)
POST*m_i	-0.011	0.010			
	(0.035)	(0.040)			
POSTTREND*m_i				-0.028	-0.023
				(0.015)	(0.016)
d_{81}*m_i			0.011		
			(0.042)		
d_{82}*m_i			-0.282		
			(0.048)		
d_{83}*m_i		0.077	-0.016		0.049
		(0.043)	(0.053)		(0.039)
d_{84}*m_i			0.012		
			(0.053)		
d_{85}*m_i			-0.073		
			(0.055)		
d_{86}*m_i			-0.192		
			(0.059)		

Notes: Dependent variable is log depreciation expenditures. Table reports results from estimating equations (35) - (38) by OLS. All regressions hospital and year fixed effects. POST is an indicator variable for the years 1984 – 1986. POSTTREND is 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986 respectively. d_t is an indicator variable for year *t*. 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. N = 40,888. In column (3), omitted category is d_{80}*m_i. To interpret the magnitudes, recall that the average Medicare share in 1983 is about two-fifths.

Table 5: The Impact of PPS on the Medicare share

	(1)	(2)	(3)	(4)	(5)
POST*m_i	-0.064	-0.065			
	(0.006)	(0.007)			
POSTTREND*m_i				-0.031	-0.032
				(0.003)	(0.003)
$d_{82}*m_i$			-0.009		
			(0.008)		
$d_{83}*m_i$		-0.004	-0.008		-0.002
		(0.007)	(0.008)		(0.006)
$d_{84}*m_i$			-0.034		
			(0.008)		
$d_{85}*m_i$			-0.085		
			(0.009)		
$d_{86}*m_i$			-0.092		
			(0.010)		

Notes: Dependent variable is Medicare share of inpatient days. Table reports results from estimating equations (35) - (38) by OLS. All regressions include hospital and year fixed effects. Data from 1980 is excluded from the analysis and for the cross-sectional variation, Medicare share of inpatient days m_i is measured in 1980 (instead of in 1983 as in other analyses). POST is an indicator variable for the years 1984 – 1986. POSTTREND is 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986 respectively. d_t is an indicator variable for year *t*. Standard errors are adjusted to allow for an arbitrary covariance matrix within each hospital over time. N = 36,611. In column (3), omitted category is $d_{81}*m_i$.

Table 6: The Impact of PPS on Technology Adoption I: Number of Facilities

	Panel A: OLS					Panel B: Conditional Fixed Effect Poisson				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
POST*m_i	2.621	2.501				0.120	0.114		0.061	0.058
	(0.357)	(0.401)				(0.015)	(0.004)		(0.007)	(0.004)
POSTTREND*m_i				1.156	1.093					
				(0.134)	(0.178)					
d_{81}*m_i			-2.423					-0.106		
			(0.526)					(0.020		
d_{82}*m_i			-2.965				-0.023	-0.138		
			(0.541)				(0.017)	(0.023		
d_{83}*m_i		-0.467	-2.281		-0.631			-0.105		-0.025
		(0.354)	(0.517)		(0.326)			(0.022		(0.008)
d_{84}*m_i			-0.496					-0.027		
			(0.567)					(0.023)		
d_{85}*m_i			1.894					0.065		
			(0.634)					(0.025		
d_{86}*m_i			0.696					0.067		
			(0.619)					(0.030		

Notes: Dependent variable is number of facilities. All regressions include hospital and year fixed effects. Mean dependent variable is 25. Left hand panel shows results from estimating equations (35) – (38) by OLS. Right hand side panel shows results from estimating the conditional fixed effect Poisson model in equation (40). POST is an indicator variable for the years 1984 – 1986. POSTTREND is 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986 respectively. d_t is an indicator variable for year *t*. 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. N = 43,188. In column (3), omitted category is d_{80}*m_i. To interpret the magnitudes, recall that the average Medicare share in 1983 is about two-fifths.

Table 7: The Impact of PPS on Technology Adoption II: Hazard models of technology adoption

	Cardiac Technologies		Diagnostic Radiology		Other technologies		Radiation Therapy (Cancer Treatment)			
	Cardiac Catheter-ization	Open Heart Surgery	CT scan	Diagnostic Radio-isotope	Neo-natal intensive care	Organ Transplant	Mega-voltage Radiation Therapy	Radio-active Implants	Therapeutic Radioisotope Facility	X-ray Radiation
Panel A: Exponential Proportional Hazard Model										
POST*m_i	1.23	2.61	0.928	0.666	3.83	1.74	1.76	-0.74	-0.096	-0.081
	(0.481)	(0.683)	(0.259)	(0.265)	(0.663)	(0.785)	(0.782)	(0.508)	(0.490)	(0.601)
d_{83}*m_i	0.24	1.48	0.769	-0.024	1.14	1.07	-1.397	-0.72	0.008	1.70
	(0.692)	(1.054)	(0.343)	(0.312)	(0.843)	(1.30)	(1.026)	(0.769)	(0.738)	(1.01)
Change in % hospitals who adopt if change POST* m_i from mean to 0	0.025	0.004	0.086	0.054	0.008	0.003	0.004	-0.021	-0.003	-0.001
Panel B: Cox Proportional Hazard Model										
POST*m_i	1.13	2.48	0.783	0.577	3.69	1.61	1.69	-0.826	-0.183	-0.188
	(0.480)	(0.680)	(0.259)	(0.266)	(0.659)	(0.783)	(0.786)	(0.511)	(0.490)	(0.601)
d_{83}*m_i	-0.795	-0.086	0.204	-0.659	0.205	0.023	-2.54	-1.598	-1.160	-0.562
	(0.510)	(0.657)	(0.300)	(0.253)	(0.641)	(0.894)	(0.725)	(0.568)	(0.513)	(0.556)
Change in % hospitals who adopt if change POST* m_i from mean to 0	0.053	0.053	0.090	0.088	0.12	0.016	0.061	-0.029	-0.002	-0.004
Mean adoption rate	0.066	0.033	0.41	0.36	0.066	0.040	0.036	0.082	0.092	0.073
N	4,861	5,130	4,739	2,758	5,301	5,437	4,950	4,542	4,485	4,741

Notes: Tables show coefficients from proportional hazard models. Censoring occurs if have not adopted by 1986. All estimates include covariates for hospital-level characteristics in 1983 (specifically, Medicare share of patient days, Medicare share of patient days squared, number of beds, and indicator variables for state, whether in an MSA, whether a general hospital, whether a short term hospital, and whether a federal hospital). Estimates based on the exponential proportional hazard model also include year fixed effects. POST is an indicator variable for the years 1984 – 1986. d_{83} is an indicator variable for year *1983.* m_i measures the Medicare share of the hospital's inpatient days in 1983. "Change in % of hospitals who adopt if change POST*m_i from mean to 0" denotes the difference in adoption (by 1986) rate if all variables are set to their mean relative to if all variables are set to their mean except for POST*m_i which is set to 0." Heteroskedasticity-robust standard errors are in parentheses. N denotes the size of the at risk sample (i.e. the number of hospitals that have not adopted in 1980). Mean adoption rate denotes the percent of the at-risk sample that adopted by 1986; note that this may differ slightly from the implied change in Figure 5 in the proportion of hospitals that have the technology between 1980 and 1986; this is because Figure 5 is done in a cross-section while the estimates in Table 7 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 Table 7 are robust to alternative ways of treating this measurement error.

Table 8: The Impact of Medicare on Log Length of Stay

	(1)	(2)	(3)	(4)	(5)
POST*m_i	-0.100	-0.102			
	(0.022)	(0.024)			
POSTTREND*m_i				-0.032	-0.030
				(0.010)	(0.011)
d_{82}*m_i			0.049		
			(0.021)		
d_{83}*m_i		-0.006	0.019		0.019
		(0.017)	(0.022)		(0.015)
d_{84}*m_i			-0.078		
			(0.028)		
d_{85}*m_i			-0.120		
			(0.032)		
d_{86}*m_i			-0.034		
			(0.035)		

Notes: Dependent variable is log length of stay; length of stay is defined as patient days / admissions. Table reports results from estimating equations (35) – (38) by OLS. All regressions include hospital and year fixed effects. Data from 1980 is excluded from the analysis and for the cross-sectional variation, Medicare share of inpatient days m_i is measured in 1980 (instead of in 1983 as in other analyses). POST is an indicator variable for the years 1984 – 1986. POSTTREND is 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986 respectively. d_t is an indicator variable for year *t.* Standard errors are in parentheses. Standard errors are adjusted to allow for an arbitrary covariance matrix within each hospital over time. N = 36,609. In column (3), omitted category is d_{81}* m_i

Table 9: The Impact of Medicare on the Share of Nurse Employment that is Skilled Nurses

	(1)	(2)	(3)	(4)	(5)
POST*m_i	3.46	3.74			
	(0.578)	(0.647)			
POSTTREND*m_i				1.58	1.67
				(0.254)	(0.272)
d_{81}*m_i			-0.280		
			(0.676)		
d_{82}*m_i			-0.575		
			(0.775)		
d_{83}*m_i		1.09	0.805		0.876
		(0.612)	(0.819)		(0.567)
d_{84}*m_i			2.40		
			(0.899)		
d_{85}*m_i			3.56		
			(0.917)		
d_{86}*m_i			4.44		
			(0.942)		

Notes: Dependent variable is RN/(RN+LPN). Table reports results from estimating equations (35) – (38) by OLS. All regressions include hospital and year fixed effects. Mean dependent variable is 70. POST is an indicator variable for the years 1984 – 1986. POSTTREND is 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986 respectively. d_t is an indicator variable for year t. 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. N = 43,162. In column (3), omitted category is d_{80}*m_i. To interpret the magnitudes, recall that the average Medicare share in 1983 is about two-fifths.

Table 10: Robustness Analysis I: Alternative Specifications

	Base Case (1)	Add linear trend * m_i (2)	Add year dummies * dep var in 82 (3)	First Differences (4)	Instrument for m_i with past values (5)	Add year * region dummies (6)	Exclude small rural hospitals (7)	Weight-ed (8)	Exclude hosps with nursing home (9)	Add POSTTREND *birthshare and d_{83}*birthshare (10)
Panel A: Dependent Variable is Capital Labor Ratio (depreciation share)										
POSTTREND*m_i	0.532	0.633	0.657	0.532	0.511	0.532	0.684	0.682	0.478	0.531
	(0.053)	(0.114)	(0.097)	(0.059)	(0.052)	(0.052)	(0.054)	(0.057)	(0.059)	(0.054)
d_{83}*m_i	-0.060	0.040	-0.068	0.064	-0.131	-0.034	0.061	-0.015	-0.208	-0.098
	(0.088)	(0.110)	(0.182)	(0.079)	(0.087)	(0.088)	(0.010)	(0.104)	(0.101)	(0.092)
N	43,188	43,188	43,041	36,900	42,428	43,188	35,339	41,024	37,466	43,181
Panel B: Dependent Variable is Log Labor Inputs (log operating expenses)										
POSTTREND*m_i	-0.068	-0.084	-0.066	-0.067	-0.067	-0.061	-0.052	-0.030	-0.086	-0.071
	(0.008)	(0.014)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.010)	(0.009)	(0.008)
d_{83}*m_i	0.022	0.006	0.023	0.007	0.034	0.024	0.044	0.054	0.020	-0.021
	(0.013)	(0.013)	(0.013)	(0.010)	(0.012)	(0.013)	(0.014)	(0.014)	(0.015)	(0.013)
N	43,188	43,188	43,041	36,900	42,428	43,188	35,339	41,024	37,466	43,181
Panel C: Dependent Variable is Log Capital Inputs (log depreciation expenses)										
POSTTREND*m_i	-0.023	0.040	-0.013	-0.019	-0.031	-0.015	0.024	0.041	-0.064	-0.028
	(0.016)	(0.033)	(0.016)	(0.017)	(0.017)	(0.016)	(0.018)	(0.022)	(0.018)	(0.017)
d_{83}*m_i	0.049	0.111	0.057	0.096	0.028	0.059	0.091	0.045	-0.002	0.035
	(0.039)	(0.042)	(0.039)	(0.034)	(0.039)	(0.040)	(0.042)	(0.044)	(0.044)	(0.039)
N	40,888	40,888	40,079	34,468	40,169	40,888	33,418	39,273	37,466	40,883
Panel D: Dependent Variable is Number of Facilities										
POST*m_i	2.501	4.254	2.267	2.478	3.010	2.041	1.260	1.560	2.313	2.50
	(0.401)	(0.731)	(0.378)	(0.427)	(0.383)	(0.406)	(0.463)	(0.613)	(0.455)	(0.411)
d_{83}*m_i	-0.467	0.410	-0.566	0.688	-0.204	-0.737	-1.521	-1.777	-0.150	-0.453
	(0.354)	(0.459)	(0.347)	(0.333)	(0.353)	(0.360)	(0.416)	(0.507)	(0.411)	(0.363)
N	43,188	43,188	43,041	36,900	42,428	43,188	35,339	41,024	37,466	43,181

Notes: Table reports results from estimating equations (36) and (38) by OLS. All regressions include hospital and year fixed effects. Dependent variable is given in panel heading POST is an indicator variable for the years 1984 – 1986. POSTTREND is 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986 respectively. d_{83} is an indicator variable for year 1983. m_i measures the Medicare share of the hospital's inpatient days in 1983. Base case includes year and hospital fixed effects. Column 2 adds linear time trend interacted with Mcrshare_83 to base case. Column 3 adds year dummies interacted with log total expenditures in 82 to base case. Column 4 redoes 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 year dummies interacted with census region dummies (nine) to base case. Column 7 excludes hospitals that are not in an MSA and that have less than 50 beds in 1983. Column 8 weights each hospital by its size (number of beds) in 1983 while excluding the top ventile by size. Column 9 excludes the 13 percent of hospitals that had a vertically-integrated nursing home unit in 1983. Column 10 adds POSTTREND*birthshare and d_{83}*birthshare, where birthshare is the share of non-Medicare patient days accounted for by newborns in 1983. Standard errors are in parentheses and are adjusted to allow for an arbitrary covariance matrix within each hospital over time.

Table 11: Estimation using within vs. between variation

	Base Case	Using only within variation	Using only between variation
	(1)	(2)	(3)
Panel A: Dependent Variable is Capital Labor Ratio (depreciation share)			
POSTTREND*m_i	0.532	0.176	0.787
	(0.053)	(0.092)	(0.044)
d_{83}*m_i	-0.060	0.041	-0.129
	(0.088)	(0.146)	(0.139)
N	43,188	43,188	43,188
Panel B: Dependent Variable is Log Labor Inputs (log operating expenses)			
POSTTREND*m_i	-0.068	-0.076	-0.062
	(0.008)	(0.010)	(0.005)
d_{83}*m_i	0.022	-0.059	0.079
	(0.013)	(0.018)	(0.014)
N	43,188	43,188	43,188
Panel C: Dependent Variable is Log Capital Inputs (log depreciation expenses)			
POSTTREND*m_i	-0.023	-0.030	-0.015
	(0.016)	(0.022)	(0.012)
d_{83}*m_i	0.049	0.031	0.067
	(0.039)	(0.050)	(0.039)
N	40,888	40,888	40,888
Panel D: Dependent Variable is Number of Facilities			
POST*m_i	2.501	2.418	2.561
	(0.401)	(0.632)	(0.404)
d_{83}*m_i	-0.467	0.135	-0.896
	(0.354)	(0.553)	(0.561)
N	43,188	43,188	43,188

Notes: Table reports results from estimating equations (36) and (38) by OLS. All regressions include hospital and year fixed effects. Dependent variable is given in panel heading POST is an indicator variable for the years 1984 – 1986. POSTTREND is 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986 respectively. d_{83} is an indicator variable for year 1983. m_i measures the Medicare share of the hospital's inpatient days in 1983. Base case includes year and hospital fixed effects. Column 2 ("using only within variation") 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 3 ("using only between variation") instruments for the variables shown 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.

Table 12: Robustness Analysis II: Alternative Dependent Variables

	Base Case	Alternative Dependent Variable I	Alternative Dependent Variable II	Alternative Dependent Variable III	Alternative Dependent Variable IV
	(1)	(2)	(3)	(4)	(5)
Panel A: Alternative Dependent Variables for Log Labor Inputs					
	Log Operating Expenditures	Log payroll expenses	Log non-payroll operating expenses	Log total employment	Log nurses
POSTTREND*m_i	-0.068	-0.067	-0.098	-0.095	-0.068
	(0.008)	(0.009)	(0.009)	(0.007)	(0.009)
d_{83}*m_i	0.022	0.011	0.018	-0.044	0.040
	(0.013)	(0.017)	(0.016)	(0.013)	(0.017)
N	43,188	43,188	43,161	43,188	43,162
Panel B: Alternative Dependent Variables for Log Capital Inputs					
	Log Depreciation	Log (interest + depreciation)	Log interest		
POSTTREND*m_i	-0.023	-0.020	0.016		
	(0.016)	(0.022)	(0.040)		
d_{83}*m_i	0.049	0.451	-0.292		
	(0.039)	(0.071)	(0.092)		
N	40,888	41,150	36,286		
Panel C: Alternative Dependent Variables for Capital Labor Ratio					
	(Depreciation/ Operating)	(Depreciation / Payroll)	(Interest + Depreciation)/ Operating	Interest / Operating	
POSTTREND*m_i	0.532	0.546	0.921	0.389	
	(0.053)	(0.069)	(0.102)	(0.067)	
d_{83}*m_i	-0.060	-0.272	-0.318	-0.258	
	(0.088)	(0.137)	(0.184)	(0.133)	
Mean dep var	4.50	6.91	7.12	2.62	
N	43,188	43,188	43,188	43,188	

Notes: Table reports results from estimating equation (38) by OLS. All regressions include hospital and year fixed effects. Dependent variable is given in column heading; first column always shows results for the dependent variable used in the main specifications above. POST is an indicator variable for the years 1984 – 1986. POSTTREND is 0 through 1983 and then takes the values 1, 2, and 3 in 1984, 1985, and 1986 respectively. d_{83} is an indicator variable for year 1983. m_i measures the Medicare share of the hospital's inpatient days in 1983. Base case includes year and hospital fixed effects. Other columns substitute alternative measures of dependent variable, as indicated. Standard errors are in parentheses. Standard errors are adjusted to allow for an arbitrary covariance matrix within each hospital over time.

Appendix Table A: Description of 113 Binary Facilities in data 1980 - 1986

Facility Description	Years in Data	Sample Mean
Abortion Services (Inpatient or Outpatient)	1980-85	0.22
Adult Day Care	1986	0.05
Acquired Immune-Deficiency Syndrome (AIDS) Services	1986	0.28
Alcoholism/Chemical Dependency Acute and Subacute Inpatient Care	1980-85	0.26
Alcoholism/Chemical Dependency Services (Outpatient)	1981-86	0.17
Ambulance Services	1980-81	0.17
Anesthesia Service	1980-81	0.72
Ambulatory Surgical Services	1981-86	0.80
Autopsy Services	1980-81	0.47
Hospital Auxiliary	1980-86	0.75
Blood Bank	1980-86	0.64
Burn Care	1980-85	0.09
Birthing Room	1985-86	0.44
Cancer Tumor Registry	1980-81	0.30
Cardiac Intensive Care	1980-85	0.67
Cardiac Catheterization	1980-86	0.16
Chaplaincy Services	1980-85	0.55
Clinical Psychology Services	1980-86	0.33
Community Health Promotion	1986	0.54
Continuing Care Case Management	1986	0.15
Contraceptive Care	1986	0.09
C.T. Scanner (Head or Body Unit)	1980-86	0.34
Day Hospital	1981-86	0.17
Dental Services	1980-85	0.48
Diagnostic Radioisotope Facility	1980-86	0.56
Diagnostic X-Ray	1985-86	0.89
Electrocardiography	1980-85	0.91
Electroencephalography	1980-81	0.50
Emergency Department	1981-86	0.85
Electromyography	1980-81	0.27
Extracorporeal Shock-Wave Lithotripter	1985-86	0.02
Family Planning	1980-85	0.10
Pharmacy Service (Full or Part Time)	1980-85	0.91
Pharmacy Unit Dose System	1980-85	0.71
Fertility Counseling	1986	0.09
Fitness Center	1986	0.09
General Laboratory Services	1980-81, 1984-85	0.88
Genetic Screening	1986	0.06
Genetic Counseling	1980-86	0.06
Geriatric Acute-Care Unit	1986	0.12
Comprehensive Geriatric Assessment Services	1982-86	0.13
Satellite Geriatric Clinics	1986	0.02
General Surgical Services	1980-81, 1983-85	0.87
Hemodialysis (Home Care/Mobile Unit)	1980-81	0.04
Histopathology Services	1980-86	0.56
Hemodialysis Services (Inpatient or Outpatient)	1980-86	0.21
Home Care Program	1980-86	0.18

Hospice	1980-86	0.08
Health Promotion	1981-85	0.40
Intermediate Care For Mentally Retarded	1980-85	0.03
Intermediate Care, Other	1980-85	0.13
Intravenous Admixture Services	1980-85	0.71
Intravenous Therapy Team	1980	0.25
Medical Library	1980-81	0.84
Megavoltage Radiation Therapy	1980-86	0.14
Medical/Surgical Acute Care	1980-85	0.91
Medical/Surgical Intensive Care	1980-85	0.74
Newborn Nursery	1980-85	0.70
Neonatal Intensive Care	1980-85	0.09
Neurosurgery	1980-81	0.29
Nuclear Magnetic Resonance Facility	1983-86	0.04
Obstetrical Care	1980-85	0.70
Occupational Health Services	1986	0.23
Open-Heart Surgery	1980-86	0.11
Organ Transplant (Including Kidney)	1980-86	0.05
Organized Outpatient Department	1981-86	0.49
Optometric Services	1981-85	0.16
Organ Bank	1980-81	0.03
Occupational Therapy	1980-86	0.40
Patient Education	1986	0.67
Patient Representative Services	1980-86	0.49
Pediatric Acute Care	1980-85	0.75
Pediatric Intensive Care	1980-85	0.18
Percutaneous Lithotripsy	1985	0.11
Pulmonary Function Laboratory	1980-81	0.58
Podiatric Services (Inpatient or Outpatient)	1980-85	0.31
Postoperative Recovery Room	1980-82	0.83
Premature Nursery	1980-85	0.26
Psychiatric Acute Care	1980-85	0.36
Psychiatric Consultation And Education	1980-86	0.29
Psychiatric Emergency Services	1981-86	0.32
Psychiatric Foster An/Or Home Care Program	1980-86	0.03
Psychiatric Intensive Care	1980-82	0.13
Psychiatric Liason Services	1983-86	0.16
Psychiatric Long-Term Care	1980-85	0.06
Psychiatric Outpatient Services	1981-86	0.18
Psychiatric Services, Pediatric	1981-86	0.14
Psychiatric Partial Hospitalization Program	1980-86	0.13
Physical Therapy	1980-86	0.79
Radioactive Implants	1980-86	0.20
Recreational Therapy	1980-86	0.30
Rehabilitation	1980-85	0.30
Rehabilitation Services (Outpatient)	1981-86	0.32
Residential Care	1980	0.05
Respit Care	1986	0.09
Respiratory Therapy	1980-86	0.81
Sheltered Care	1981-85	0.02

Self Care	1980-85	0.06
Long Term-Skilled Nursing	1980-85	0.16
Social Work Services	1980-85	0.77
Speech Therapy	1980-86	0.36
Other Special Care	1981-85	0.22
Sports Medicine Clinic/Service	1986	0.11
Sterilization	1986	0.23
Toxicology/Antidote Information	1980-81	0.38
Tuberculosis And Other Respiratory Diseases	1980-86	0.34
Therapeutic Radioisotope Facility	1980-86	0.21
Trauma Center	1984-86	0.17
Ultrasound	1981-86	0.69
Volunteer Services	1980-86	0.65
Women's Center	1986	0.09
Worksite Health Promotion	1986	0.35
X-Ray Radiation Therapy	1980-86	0.16

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 – 1985 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 1980-1983, 1985 if hospital reports having alcohol/chemical dependency inpatient care.
3. C.T. Scanner (Head or Body Unit): coded 1 in 1980 and 1981 if the hospital reports having either a C.T. Scanner Head Unit or a C.T. Scanner Body Unit or both; coded 1 1982 – 1986 if the hospital reports having a C.T. 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 1982-1985 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 – 1986 if hospital reports having hemodialysis services.
6. Organ Transplant (Including Kidney): coded 1 in 1980-1985 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.