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Medicare Reimbursement, Nurse Staffing, and Patient Outcomes*

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Introduction

The quality of health care is an issue of significant concern for our society. Many Americans believe that the quality of health care is poor and that the quality of care has decreased over the last several years (Employee Benefit Research Institute 2004; Kaiser Family Foundation 2004a). Moreover, concern about the quality of health care is not limited to the lay public. The Institute of Medicine (IOM) issued a series of influential reports on the quality of health care in the United States that portrayed a grim picture: “Quality problems are everywhere, affecting many patients. Between the health care we have and the care we could have lies not just a gap, but a chasm (Committee on Quality of Health Care in America 2001, p. 1).” Indeed, the IOM (Kohn et al. 1999) claim that medical errors result in 98,000 unnecessary deaths per year in the United States has received considerable media attention and it has become a rallying cry for professional organizations such as the Leapfrog Group whose mission is to improve the quality of health care.¹

Casual empiricism also suggests that there is a health care “quality” problem in the US. Per capita spending on health care in the United States is more than twice the median of OECD countries, but measures of population health show the United States to be ranked relatively low internationally (Reinhardt et al. 2002; World Health Organization 2004). More sophisticated empirical analyses also suggest a “quality” problem; several studies of the association between spending on health care and health reveal a remarkably weak correlation (Newhouse 1993; Friedman 2000; Skinner et al. 2001; Levy and Meltzer 2001).

Interestingly, the cause of the quality problem highlighted by studies relating spending on health care to health is fundamentally different from the cause of the quality problem perceived by the general public. For example, the RAND Health Insurance Experiment provides what may be the most compelling evidence that a significant amount of spending on health care has little health benefit (Newhouse 1993).

¹ In the first two weeks after the IOM (Kohn et al. 1999) report on medical errors was published, there were 72 newspaper articles covering the story that explicitly cited the 98,000 figure according to the NewsBank, Inc. index (<http://www.newsbank.com/>). Even in 2004, the IOM figure of 98,000 deaths due to medical errors continues to be a major influence on public opinion, as there have been 151 newspaper articles citing this figure.

This suggests that there is a considerable amount inefficient spending and too much utilization of low-value services. In contrast, public opinion about the quality of health care is closely tied to views of managed care, and in this case, the public is concerned that providers may respond to supply side rationing by limiting utilization and providing too little care (Kaiser Family Foundation 2004b).²

Supply side factors, in particular inadequate provider payments, are a cause of concern about the quality of health care in our public systems. Advocates for the poor worry about the quality of care received by Medicaid recipients because of inadequate provider payments. Medicaid payments are notoriously low and state policymakers continue to use payments to medical providers more as a fiscal tool than a health policy tool.³ In 2004, all 50 states either froze or reduced Medicaid payments to at least one group of medical providers in response to budgetary pressures (Kaiser Family Foundation 2004c). Similarly, Medicare recipients and advocates for the elderly are concerned about the quality of care because of the federal government's use of provider payments as a way to control Medicare costs, particularly payments to managed care organizations and nursing homes.⁴

The fear that inadequate private and public payments to medical providers are adversely affecting the quality of health care is well founded. There is abundant evidence that providers respond to financial incentives by altering their treatment practices or case mix (Hillman 1990; Hemenway 1990; Kessler and McClellan 1996; Yip 1998; McGuire 2000; Gaynor et al. 2001; Santerre 2002; Barro and Beaulieu 2003). Indeed, providers are explicit on this point. A recent report by the American Medical Association (AMA) had this to say: "Significant numbers of physicians are adjusting the resource content of services in response to the growing gap between Medicare's payment updates and physicians' practice costs (AMA 2002)." Thus, limiting or reducing provider payments will likely alter treatment, for example reduce the

² A recent public opinion poll reported that only 32% of Americans believe that managed care companies are doing a good job serving their patients, and the same survey reported that nearly 60% of Americans are worried that their managed care company will put profits before their health (Kaiser Family Foundation 2004b).

³ See Zuckerman et al. 2004 for an analysis of Medicaid fees.

⁴ See Berenson and Dowd (2002) for a discussion of the problems associated with financing of Medicare managed care plans.

amount of care or change the types of care received, and as a result, may adversely affect health outcomes.

Surprisingly, empirical evidence to support this hypothesis is scarce. For example, two recent reviews by Miller and Luft (2002, 1997) conclude that managed care (versus fee-for-service) does not adversely affect health even though there is evidence that managed care was effective at reducing payments to providers and reducing utilization (Glied 2000, Cutler et al. 2000). Studies of Medicare and the switch to a Prospective Payment System (PPS) reveal mixed evidence as to the effect of the PPS on health even though it is clear that the switch to a PPS decreased hospital length of stay, and in the case of nursing homes decreased nursing resources (Hodgkin and McGuire 1994; Cutler 1995; Ellis and McGuire 1996; Grabowski 2001; Konetzka et al. 2004).⁵

Overall, the evidence is not strong that reductions in provider payments have adversely affected the quality of care. While it seems clear that providers respond to changes in payments by altering treatment and care in ways that are consistent with profit (surplus) maximization, it is not clear that those changes in treatment and care significantly affect health. In fact, decreases in provider payments may be welfare improving if they serve mainly to eliminate low-quality care—a conclusion that is consistent with the evidence pertaining to the transformation of the US health care market from fee-for-service to managed care. Of course, the general public, providers, and patient advocates disagree with this hypothesis. On the other hand, state governments have consistently kept Medicaid payments remarkably low, perhaps because of the lack of (perceived) evidence that cuts in provider payments are harmful, although this strategy may have more to do with fiscal policy than health policy.

In sum, the effect of provider payments on the quality of health care is an important and unsettled issue. A critical issue is whether changes in provider payments affect health (i.e., outcomes). On this question there is limited evidence, and the purpose of this paper is to provide more. Specifically, we study the effect of plausibly exogenous changes in Medicare reimbursement—caused by geographical

⁵ There are only two published studies of the effect of Medicaid fees on health; both examine the effect of fees on infant health and both find that lower fees adversely affect infant health (Currie et al. 1995; Gray 2001).

reclassification—on hospital staffing (nurses) and patient outcomes. Our study may be particularly valuable because as Cutler (1995) and others note, Medicare reimbursement rates were quite generous during the period when PPS was implemented and when most of the previous research on this issue was conducted. In contrast, during the period we study, 1994-2001, Medicare reimbursement levels were lower than in the earlier periods. Therefore, changes in reimbursement may be more important and have larger impacts in the more recent period. To measure the effects of interest, we use a quasi-experimental research design based on a pre- and post-test with comparison group approach. The treatment group is hospitals that are geographically reclassified, which leads to changes in Medicare reimbursement rates of about 10% on average. The comparison group is either hospitals in the area of reclassification (destination), or hospitals in the originating geographical area. Using these groups, we compare changes in outcomes surrounding the change in reimbursement.

Theoretical Considerations

We begin with a simple model of hospital behavior in which hospitals treat two types of patients defined by third-party payer status: public (e.g., Medicare) and private. We also assume that the hospital has two objectives: to make money (profits) and to provide quality care to each of the two types of patients. The assumption that hospitals care about objectives other than profit is standard reflecting the large share of hospitals that are not-for profit (Hodgkin and McGuire 1994, Newhouse 1970). We can relax this assumption later to investigate possible differences between for-profit and not-for-profit hospitals. The following utility function describes the objective function of the hospital:

$$(1) U = U(\pi, I_1, I_2),$$

where π is used to represent profits and I_i is used to represent quality of care for patient type i (1 =public, 2 =private). Quality of care depends on the intensity (quantity) of resources dedicated to each patient and so it is per patient quality and the per-patient quantity of resources that is of interest. Here we assume that

there are two inputs: nurses per patient (N) and physicians per patient (D). The patient-specific production functions of quality are given by:

$$(2a) I_1 = I_1(N_1, N_2, D_1)$$

$$(2b) I_2 = I_2(N_1, N_2, D_2)$$

$$I_{1N1} > I_{1N2} > 0, I_{1N1N2} = 0, I_{1N1Ni} < 0, I_{1N2} = I_{2N1}$$

$$I_{1D1} = I_{2D2} = I_D > 0, I_{DD} < 0$$

Note that in equations (2a) and (2b), we assume the quality production function is the same for public and private payers. We also assume that nurses allocated to public (private) patients affect the quality of care of private (public) patients. This would be the case if some part of nurse's effort, for example the monitoring of vital statistics using common monitoring equipment, results in joint production.⁶

Some may object to the assumption that patients receive different quality of care depending on payer status. However, there is some empirical evidence that suggests this to be the case. For example, Doyle (2005) found that trauma patients received different amounts of care, as measured by length of stay, number of procedures, and total charges, depending on payer status, and that these differences in care resulted in differential mortality. In this case, quality was different because of different lengths of stay and because of different intensity of treatment (number of procedures). Interestingly, the different number of procedures and different intensity of treatment would require different amount of nursing resources. Thus, there would be a different number of nurses (or other resources) assigned to a floor (unit) depending on the payer mix of the patients. So this provides a plausible mechanism for nursing resources to be allocated on a patient-type basis.

Hospital profits are a function of revenues and costs. Revenues depend on the payments made to the hospital for each type of patient, and hospitals are assumed to be price takers. Payments made on behalf of public patients do not depend on the quality of care, but private payers are willing to pay for quality (i.e., there is a schedule of payments for each level of quality).

$$(3) P_2 = \alpha + \beta I_2(N_1, N_2, D_2)$$

⁶ See Glazer and McGuire (2002) for a related analysis of the effect of joint production.

We assume that patients do not pay for care (they are fully insured) and that the quantity of patients depends only on per patient quality of care. Patient demand functions are as follows:

$$(4a) X_1 = f_1(N_1, N_2, D_1),$$

$$(4b) X_2 = f_2(N_1, N_2, D_2)$$

$$f_{1N_1} > f_{1N_2} > 0, f_{1N_1N_2} < 0, f_{1N_1N_2} = 0, f_{1D_1} = f_{2D_2} = f_d > 0, f_{DD} < 0$$

Here again, we assume that the demand curve of public and private patients is the same and that both patients respond to quality in the same way.⁷

Average costs are a function of the quantity of patient-specific resources used to produce patient quality. The wage of nurses is denoted by w and the wage of physicians is denoted by r . Total costs (TC) are given by:

$$(5) \quad TC = wN_1X_1 + wN_2X_2 + rD_1X_1 + rD_2X_2 \\ = (wN_1 + rD_1)f_1(N_1, N_2, D_1) + (wN_2 + rD_2)f_2(N_1, N_2, D_2)$$

Total costs are the average cost of each patient type (e.g., wN_1+rD_1) times the quantity of each patient type. Note that in equation (5), the cost of nurses allocated to private patients does not affect the cost of public patients. Given these relations, hospital profit will be:

$$(6) \quad \pi = P_1f_1(N_1, N_2, D_1) + [\alpha + \beta]f_2(N_1, N_2, D_2) - \\ (wN_1 + rD_1)f_1(N_1, N_2, D_1) - (wN_2 + rD_2)f_2(N_1, N_2, D_2)$$

From the hospitals perspective, profits are determined by the choice of nurses (N) and physicians (D) per patient (type) given the payment and technological constraints the hospital faces. The relationships between profits and changes in nurses (N) and physicians (D) are given by:

⁷ A more developed model would consider competitive issues and specifically, the quality produced by other providers. Here we implicitly assume that quality of care of other providers is being held constant. This is consistent with our empirical analysis that examines changes in Medicare reimbursement that are provider specific. So not all providers will be changing quality in response to changes in reimbursement—only those affected by changes in Medicare reimbursement.

$$(7a) \frac{\partial \pi}{\partial N_1} = P_1 f_{1N_1} + \beta_{12N_1} X_2 + [\alpha + \beta_2] f_{2N_1} - w(X_1 - N_1 f_{1N_1} - N_2 f_{2N_1})$$

$$(7b) \frac{\partial \pi}{\partial N_2} = P_1 f_{1N_2} + \beta_{2N_2} X_2 + [\alpha + \beta_2] f_{2N_2} - w(N_1 f_{1N_2} - X_2 - N_2 f_{2N_2})$$

$$(7c) \frac{\partial \pi}{\partial D_1} = P_1 f_D - r(X_1 - D_1) f_D$$

$$(7d) \frac{\partial \pi}{\partial D_2} = \beta_D X_2 + [\alpha + \beta_2] f_D - r(X_2 - D_2) f_D$$

Equations (7a) through (7d) are the familiar relationships between marginal revenue and marginal cost. If the firm's objective function consisted solely of profit, these equations would be the first order conditions for profit maximization. However, maximizing the hospital objective function with respect to profits and quality of care yields the following first order condition for nurses allocated to public patients (N_1):

$$\begin{aligned} \frac{\partial U}{\partial N_1} &= \frac{\partial U}{\partial \pi} \frac{\partial \pi}{\partial N_1} + \frac{\partial U}{\partial I_1} I_{1N_1} + \frac{\partial U}{\partial I_2} I_{2N_1} = 0 \\ \frac{\partial \pi}{\partial N_1} &= P_1 f_{1N_1} + \beta_{12N_1} X_2 + [\alpha + \beta_2] f_{2N_1} - w(X_1 - N_1 f_{1N_1} - N_2 f_{2N_1}) \end{aligned}$$

(8) so

$$\frac{\partial U}{\partial N_1} = P_1 f_{1N_1} + \beta_{12N_1} X_2 + [\alpha + \beta_2] f_{2N_1} + \left[\left(\frac{\partial U}{\partial I_1} I_{1N_1} + \frac{\partial U}{\partial I_2} I_{2N_1} \right) / \frac{\partial U}{\partial \pi} \right] = w(X_1 + N_1 f_{1N_1} + N_2 f_{2N_1})$$

and for nurses allocated to private patients (N_2),

$$\begin{aligned} \frac{\partial U}{\partial N_2} &= \frac{\partial U}{\partial \pi} \frac{\partial \pi}{\partial N_2} + \frac{\partial U}{\partial I_1} I_{1N_2} + \frac{\partial U}{\partial I_2} I_{2N_2} = 0 \\ \frac{\partial \pi}{\partial N_2} &= P_1 f_{1N_2} + \beta_{2N_2} X_2 + [\alpha + \beta_2] f_{2N_2} - w(N_1 f_{1N_2} - X_2 - N_2 f_{2N_2}) \end{aligned}$$

so

$$(9) \frac{\partial U}{\partial N_2} = P_1 f_{1N_2} + \beta_{2N_2} X_2 + [\alpha + \beta_2] f_{2N_2} - w(N_1 f_{1N_2} - X_2 - N_2 f_{2N_2}) + \left[\left(\frac{\partial U}{\partial I_1} I_{1N_2} + \frac{\partial U}{\partial I_2} I_{2N_2} \right) / \frac{\partial U}{\partial \pi} \right] = 0$$

$$\frac{\partial U}{\partial N_2} = P_1 f_{1N_2} + \beta_{2N_2} X_2 + [\alpha + \beta_2] f_{2N_2} + \left[\left(\frac{\partial U}{\partial I_1} I_{1N_2} + \frac{\partial U}{\partial I_2} I_{2N_2} \right) / \frac{\partial U}{\partial \pi} \right] = w(N_1 f_{1N_2} + X_2 + N_2 f_{2N_2})$$

The first order condition for physician services (D_1) allocated to public patients is:

$$\begin{aligned} \frac{\partial U}{\partial D_1} &= \frac{\partial U}{\partial \pi} \frac{\partial \pi}{\partial D_1} + \frac{\partial U}{\partial I_D} I_D = 0 \\ (10) \quad \frac{\partial \pi}{\partial D_1} &= P_1 f_D - r(X_1 - D_1) f_D, \\ \text{so} \\ \frac{\partial U}{\partial D_1} &= P_1 f_D + \left(\frac{\partial U}{\partial I_D} I_D / \frac{\partial U}{\partial \pi} \right) = r(X_1 + D_1) f_D \end{aligned}$$

and the first order condition for physician services (D_2) allocated to private patients is:

$$\begin{aligned} \frac{\partial U}{\partial D_2} &= \frac{\partial U}{\partial \pi} \frac{\partial \pi}{\partial D_2} + \frac{\partial U}{\partial I_D} I_D = 0 \\ (10) \quad \frac{\partial \pi}{\partial D_2} &= \beta_{1D} X_2 + [\alpha + \beta_{12}] f_D - r(X_2 - D_2) f, \\ \text{so} \\ \frac{\partial U}{\partial D_2} &= \beta_{1D} X_2 + [\alpha + \beta_{12}] f_D + \left(\frac{\partial U}{\partial I_D} I_D / \frac{\partial U}{\partial \pi} \right) = r(X_2 + D_2) f \end{aligned}$$

We will now use these first order conditions to discuss the implications of a change in public payment levels on hospital behavior.

Change in Public Reimbursement Level

From equation (8), we see that the number of nurses allocated to public patients depends on the following: public and private payment levels; the productivity of nurses in creating patient demand; the productivity of nurses in producing quality; the utility that nurses produce because of their contribution to quality; and the costs of nursing resources. An increase in public payment levels (P_1) will make public patients more profitable and the hospital will want to increase the number of public patients, which can only be done by increasing quality. Therefore, the firm will hire more nurses to increase the quality of care for public patients. More nurses allocated to public patients, however, will also increase the quality provided to private patients, which will increase the number of private patients and private payments since private payers reimburse quality.

If there was no joint production, the increase in the number of nurses would be smaller and the increase in quality smaller; the joint production of quality across patient types exacerbates the effects of a change in Medicare reimbursement. Moreover, a hospital with a greater share of Medicare patients will experience a smaller change in quality (i.e., resources per patient) than a hospital with fewer Medicare patients because there are fewer spillovers between public and private patients. When the Medicare share is relatively high, it is more difficult for the firm to attract additional public patients by raising quality, so quality will increase by a smaller amount, and there will be fewer spillovers. Glazer and McGuire (2002) have a similar result, which they refer to as dilution; the effects of changes in Medicare reimbursement on quality are mediated (muted) by changes in the quality of care provided to private payers, and a larger share of Medicare patients results in less dilution of the effects of Medicare reimbursement. This is a result of their assumption that there is a common level of quality across patient types. So the difference between our model and that of Glazer and McGuire (2002) is testable. In our model, hospitals with a larger share of Medicare patients should see smaller changes in quality in response to changes in Medicare reimbursement, whereas in Glazer and McGuire (2002) the opposite is predicted.

From equation (10), we also see that an increase in public reimbursement levels will increase the quantity of physician resources for similar reasons, although in this case, an increase in physician resources dedicated to public patients does not increase private patient quality. Therefore, there should be a relative increase in the quality of care to public relative to private patients. If, like physician resources, nursing resources were also patient-specific, then an increase in public payment levels would not have any effect on private payer quality, or the number of private patients. The point is that changes in Medicare payments will have larger effects on quality of care for Medicare patients than for private patients as long as there are some resources used to produce quality that are patient-specific. If all resource uses are patient-specific, then changes in Medicare payments will have no effect on private patient quality.

There also may be systematic differences between for-profit and not-for-profit hospitals. If we assume that the objective function of for-profit hospitals depends only on profit, then the for-profit

hospital will choose nurses and physicians according to equations (7a) through (7d). Comparing equations (7) to (8) indicates that the for-profit hospital will choose fewer nurses and physicians (per patient) than not-for-profit hospitals, serve fewer patients and produce lower quality of care.⁸ The reason for this is that the for-profit does not value quality directly and therefore will produce less quality. This prediction is consistent with the observed smaller size of for-profit hospitals (David 2003). Moreover, an increase in public payments will result in a smaller increase in nurses and the quality of care in for-profit hospitals than in not-for-profit hospitals.

To summarize, this simple model of hospital behavior predicts that an increase (decrease) in public payment levels will have the following effects:

- increase (decrease) the quantity of nurses per patient;
- increase (decrease) the quantity of both public and private patients;
- increase (decrease) the quantity of physician services dedicated to public patients;
- and an increase (decrease) in the quality of care for both public and private patients with a relatively larger increase (decrease) in quality for public patients.

The model also predicts that if nursing (and all other) resource uses are patient-specific, then an increase in public payments will have no effect on private patients. In addition, if the objectives of for-profit and not-for-profit hospitals differ in their valuation of quality, for-profit hospitals will produce lower quality care and see fewer patients than not-for-profits, and changes in public payments will have smaller effects on input demands and quality. Finally, hospitals with a relatively large share of Medicare patients should respond less to changes in Medicare reimbursement than hospitals with a smaller share of Medicare patients.

Medicare Reimbursement and Health- Previous Literature

There have been relatively few studies that have examined the effect of changes in Medicare reimbursement on health, and most of these have focused on the changes brought about by the switch to a PPS in 1983. It is important to note that a switch to PPS changes hospital reimbursement in two ways: it

⁸ There is little empirical evidence that not-for-profit hospitals produce higher quality care, although the empirical problems associated with identifying such differences are significant (Keeler et al. 1992; Sloan et al. 2001; Chou 2002).

changes the marginal reimbursement for additional services (e.g., inpatient day), and it changes the average reimbursement. Some studies examined the combined effect of such a change on mortality, for example Rogers et al. (1990), while others have attempted to isolate each effect separately, for example Cutler (1995). Our analysis focuses on changes in average payments, and in this regard is most similar to Staiger and Gaumer (1995). Changes in average payments are most relevant for policy today because of the likelihood that the prospective PPS will remain intact for the foreseeable future.

In a series of influential papers, Rogers and colleagues (Rogers et al. 1990; Kahn et al. 1990; Kosecoff et al. 1990) examined patient health (adjusted for health at admission) using a nationally representative sample of Medicare patients pre- and post-PPS. Findings from these studies show no increase in mortality (in-hospital, 30-day, and 180-day) subsequent to the switch to the PPS, although the authors do report an increase in the number of patients discharged in an unstable condition (Kosecoff et al. 1990). One problem with this series of papers is that they are basically before and after analyses and are therefore unable to control for time-varying influences that may be confounding their results. This is likely to have been problematic since as these papers and others (e.g., Hodgkins and McGuire 1994) demonstrate, there were significant trends in mortality and treatment at this time.

Cutler (1995) also finds that the introduction of the PPS had no long-run effect on mortality of the elderly treated for severe illnesses. However, Cutler separates the PPS effect into that due to changes in marginal reimbursement and that due to changes in average reimbursement. He finds that the marginal reimbursement effect is health improving: moving to a prospective payment system reduces mortality, which is inconsistent with theory. Cutler (1995) argues that most of this effect is due to selection—less sick patients post PPS. For changes in average reimbursement, Cutler (1995) finds that decreases in payments compress the mortality distribution: increase in-hospital mortality, decrease post discharge mortality, and leave one-year mortality unchanged. Cutler (1995) avoids the weakness of the simple pre- and post-PPS research design by exploiting the fact that Massachusetts implemented PPS later than other

state in New England. So the underlying identification assumption of Cutler (1995) is that unmeasured trends in mortality in Massachusetts were the same as those in other New England States.⁹

As noted, the study that is closest to ours is by Staiger and Gaumer (1995). These authors use plausibly exogenous variation in Medicare reimbursement rates in the post-PPS period to examine the effect of reimbursement on mortality of Medicare patients treated for urgent care and heart attacks. Also like us, Staiger and Gaumer (1995) include hospital fixed effects and examine changes in mortality within hospitals pre- and post-changes in Medicare reimbursement. In their case, changes in Medicare reimbursement stem mainly from the fact that the PPS was phased in over a five-year period, which created hospital-specific variation in reimbursement levels during this period. Estimates in Staiger and Gaumer (1995) suggest that changes in reimbursement have decidedly mixed effects. Reductions in Medicare payments increase mortality (45 day), but mostly for government hospitals, and to a lesser extent for-profit hospitals. In the case of not-for-profit hospitals, which are the majority of hospitals, reductions in reimbursement are not significantly related to mortality. For all types of hospitals, reductions in Medicare reimbursement have no statistically significant effects on one-year mortality.

Staiger and Gaumer (1995) assume that hospitals care about average patient quality and that the hospital does not differentiate between patients in terms of quality. This leads them to scale the Medicare reimbursement rate by the share of hospital revenues due to Medicare to create what they refer to as the Medicare “bite.” The hypothesis is that the larger the “bite”—changes in hospital revenues—the larger the effects on outcomes, but as noted, this assumes that hospitals are unable to alter quality by patient type. An alternative model in which hospitals can produce different quality by patient type (Medicare v non-Medicare) still leads to the conclusion that changes in Medicare reimbursement will affect quality (e.g., mortality) of care for Medicare patients, but in this case the effect will not differ by the share of hospital revenues due to Medicare. In addition, changes in Medicare reimbursement will have no effect

⁹ Due to data limitations, estimates of the effect of changes in average reimbursement in Cutler (1995) are specific to Massachusetts.

on non-Medicare patients. Unfortunately, the empirical specification used by Staiger and Gaumer (1995) do not allow them to investigate this hypothesis.

The most recent study of the issue is by Shen (2003) and this paper is very similar to the paper by Staiger and Gaumer (1995). Shen (2003) limits the analysis to Medicare patients treated for acute myocardial infarction (AMI) and uses a measure of the Medicare “bite” as her key explanatory variable. She finds that reductions in Medicare reimbursement increase short-term mortality, but leaves one-year mortality basically unchanged.

This brief literature review leads to a few conclusions. First, for such an important issue, there is relatively little research examining the effect of Medicare reimbursement on health. Second, results are mixed, although most studies find that reductions in Medicare reimbursement rates compress the mortality distribution. Third, the range of outcomes examined have been quite limited and basically restricted to mortality and readmission. Fourth, no study has used a research design that uses hospitals in close geographic proximity as comparisons. This may be important given that there is a great deal of geographic variation in hospital treatment practices and health outcomes, and even studies that use fixed effects methods such as Staiger and Gaumer (1995), are unable to control for time-varying area effects. Finally, no prior study has examined whether changes in Medicare reimbursement has spillover effects on other patients. In this paper, we add to the evidence of the effect of changes in Medicare reimbursement on health, and we try to extend the literature by examining a broader range of outcomes; by using geographically close hospitals as controls; and by explicitly investigating whether there are spillover effects.

Research Design and Methods

Our objective is to obtain estimates of the effect of changes in Medicare reimbursement on hospital use of nursing resources and patient outcomes. While Medicare reimbursement levels change from year-to-year, these changes are mostly determined by national and regional factors that do not vary significantly within MSA (region) over time. For example, all hospitals in the same MSA will receive the

same year-to-year increases in Medicare reimbursement due to local variation in labor costs, which do not exhibit much geographic variation. This component is referred to as the operating wage index.

Moreover, much of the remaining variation in year-to-year increases in Medicare reimbursement has a national component (changes in DRG weight) that is common to all hospitals in the country. So analyses that hold constant differences in outcomes due to geography and time would leave little variation in Medicare reimbursement that could be exploited to identify effects of reimbursement on hospital resource use and patient outcomes. Previous studies have addressed this issue by using the variation in reimbursement brought about by introduction of the PPS system, but since this introduction, there has been little significant variation in Medicare reimbursement.

Geographic Reclassification

One source of variation in Medicare reimbursement is due to geographic reclassification. Hospitals can be reclassified to areas that receive higher Medicare reimbursement (operating wage index and standard payment). To qualify for such reclassification, a hospital has to meet two criteria.¹⁰ First, the hospital has to be within a specified number of miles of the target area: 15 miles for a metropolitan hospital and 35 miles for a non-metropolitan hospital. The hospital may still qualify for reclassification if it does not meet the proximity standard if at least half of the hospital's employees reside in the target area. Second, the metropolitan (non-metropolitan) hospital's wages have to be eight (six) percent higher than the average wages in its assigned area and its wages have to be at least 84 (82) percent of the target area's average wage.¹¹ Rural and sole community hospitals can be reclassified by meeting less stringent criteria. Thus, hospitals that are most likely to be reclassified are those that are near, but not in, more densely-populated and therefore higher wage areas, and rural hospitals. Hospitals apply for reclassification at least one year before reclassification will take effect, and they know the outcome of the reclassification

¹⁰ The information about reclassification regulation is taken from the testimony before Congress of William Scanlon, Director of Health Care Issues for the General Accounting Office (Scanlon 2002).

¹¹ Note that this limits the size of the increase to between 8 (6) and 16 (18) percent. In our data, the average change in the operating wage index for hospitals changing classification is approximately 10 percent.

application at least six months in advance of it taking effect. Prior to 2002, reclassification was valid for one year and hospitals had to apply every year to maintain the reclassification. Many hospitals that obtain reclassification subsequently lose their status because they cannot meet the wage requirements. These hospitals, which we refer to as declassified hospitals, also experience significant changes in reimbursement, which we exploit.

The geographic reclassification process has a few empirical implications. First, since hospitals know at least six months in advance that they will be receiving an increase in Medicare reimbursement, they may begin to respond immediately—prior to reclassification becoming effective. The empirical analysis should take this into account, which we do by examining changes between year $(t-2)$ and (t) . Second, many reclassifications are temporary and hospitals responses may be smaller than if the change was permanent. Among hospitals that changed geographic area, 40% were reclassified for only one year and 70% were reclassified for two or less years. Third, and perhaps most importantly, is the question of whether meeting the criteria is exogenous; conditional on observed characteristics, is reclassification unrelated to hospital resource use and patient outcomes?

To qualify for reclassification, the hospital has to have unusually high labor costs for its area. This may be purely a result of geography, which is consistent with the intent of the reclassification regulation, and thus conditioning on geography and year may be sufficient to plausibly establish exogeneity. However, it would require conditioning on a geographic level that is difficult to identify—hospitals in a given proximity to a Medicare reimbursement boundary. And more importantly, there may be few hospitals meeting such a definition in any given year. It is also likely that high labor costs may be due to systematic differences in hospital preferences or characteristics. For example, a hospital that has a strong preference for quality may employ higher quality employees that are more expensive. In this case, it is necessary to control for hospital specific effects to bolster the case for exogeneity. Hospital fixed effects account for any time invariant characteristics of the hospital that are correlated with reclassification status, and staffing and patient outcomes. Thus, if unmeasured time-invariant factors are the source of endogeneity, the fixed effects procedure is effective at controlling for this problem. Given

that most hospitals enter the data for only one experimental period (pre- and post-classification), most characteristics of the hospital will be relatively stable and the identifying assumption underlying the fixed effects specification gains in plausibility.

Empirical Specification

Our research design, which is based on a multivariate regression, is motivated by a desire to support the assumption that changes in Medicare reimbursement due to geographic reclassification are exogenous. Accordingly, we selected the sample and specified the regression model in ways consistent with this objective. First, we chose a sample that consists of a group of hospitals that were reclassified, or that lost reclassification status (declassified), in year (t) and a group of hospitals in the same geographic area and year that did not change status. We refer to hospitals changing status as treatments and the hospitals not changing status as controls. For each hospital, treatments and controls, we include two years of information: one from year (t-2), which is before reclassification, and one from year (t), which is after reclassification. Then, as noted above, to bolster the exogeneity assumption, we control for either geographic area-year, or hospital fixed effects and year.

To make things concrete, consider the following regression model that relates the number of registered nurses (RN), which is measured at the hospital level, to whether a hospital was reclassified.

$$RN_{ijt} = \beta_0 + \beta_1 TREAT_i + \beta_2 POST_t + \beta_3 (TREAT_i \times POST_t) + X_{it} \Gamma + \delta_{jt} + u_{ijt}$$

(1) $i = 1, \dots, N$
 $j = 1, \dots, M$
 $t = 1994, \dots, 2001$

In equation (1), the variable TREAT is an indicator (equal to one and zero otherwise) of whether a hospital was reclassified; POST is an indicator of whether the observation is post-reclassification; the vector (X) represents measured characteristics of the hospital, for example number of beds (hospital and nursing home units), number of inpatient admissions (hospital and nursing home units), number of outpatient visits, whether it was a teaching hospital and whether it is a for-profit hospital. It is important

to hold constant the quantity of patients as it is per-patient resources that are the measure of interest. We describe these measures in more detail in the data section. Equation (1), also includes controls for geographic area-year effects (δ_{jt}). The geographic unit is the area used by Medicare to establish different reimbursement rates, and these are primarily urban areas (MSAs) in a state with all non-urban areas (i.e., rural areas) combined into one geographic unit. We allow each geographic area to have a separate effect in each year. For example, assume that in 1998 a hospital outside of Chicago was reclassified into the Chicago area for Medicare reimbursement purposes. So this hospital would contribute two observations: one in 1996 and one in 1998. We would also include other hospitals in the originating (or alternatively the destination) geographic area and each of these would contribute two years of information: 1996 and 1998.

In equation (1), we control for all geographic area-year combinations such as that described for this Chicago-area hospital. Thus, we are comparing treatment hospitals to control hospitals in the same area and year. Thus, there would be very little independent variation in the operating wage index unless some hospitals were reclassified. The average change in the operating wage index following reclassification is approximately 10 percentage points, which is approximately a 10 percent change.

The identification assumption underlying equation (1) is that by controlling for geographic area-year, we have controlled for any unmeasured characteristics of hospitals that would make reclassification endogenous—related to hospital staffing and patient outcomes. We acknowledge that this assumption is unlikely to hold particularly since our definition of geographic unit is larger than that consistent with the reclassification process. Ideally, we would like to compare hospitals on the urban fringe of say Chicago to similar hospitals, but there may be few hospitals in the same radius as the hospital of interest. More importantly, why would one hospital in a given radius of Chicago reclassify and another not? It is likely that these hospitals differ in unmeasured ways that affect staffing and patient outcomes.

An alternative is to control for hospital-specific effects. This is illustrated by equation (2) below:

$$\begin{aligned}
(2) \quad & RN_{ijt} = \alpha_i + \beta_2 POST_t + \beta_3 (TREAT_i \times POST_t) + X_{it} \Gamma + \delta_t + u_{ijt} \\
& i = 1, \dots, N \\
& j = 1, \dots, M \\
& t = 1994, \dots, 2001
\end{aligned}$$

Note that in equation (2) there is a hospital-specific effect (α_i) included in the model.¹² And now we control for just year (δ_t) and not geographic area-year. Here, the identification assumption is that once we control for the hospital-specific effect, treatment status is exogenous. This is a more plausible assumption than that underlying equation (1). The threat in this case is that there are unmeasured, time-varying hospital characteristics that affect outcomes that do not operate through changes in reimbursement. The conditional nature of this statement is important to recognize. Reclassification will change reimbursement and this may affect hospital staffing and patient outcomes. This is not a problem and is in fact the identification we seek to exploit.

However, it is even possible to include hospital fixed effects and geographic area-year effects, although in this case, year refers to the year of reclassification and not each year that data is observed. This specification is given by equation (3):

$$\begin{aligned}
(3) \quad & RN_{ijt} = \alpha_i + \beta_2 POST_t + \beta_3 (TREAT_i \times POST_t) + X_{it} \Gamma + \delta_{jt} + u_{ijt} \\
& i = 1, \dots, N \\
& j = 1, \dots, M \\
& t = 1994, \dots, 2001
\end{aligned}$$

In this specification, we control for unmeasured, hospital-specific effects (α_i), and time-varying effects at the geographic area-year level. To be clear about this specification it helps to consider a case where there are only four hospitals, one treatment and three control, and all are from the same area. Thus there are eight observations: two years (pre- and post-reclassification) of data for four hospitals. Our model would include the following six variables: four dummy variables identifying each hospital, the operating wage index, and a dummy variable indicating the post-reclassification year. In this case, the dummy

¹² For hospitals that “switch” (or are “controls”) more than once, we treat that hospital as a separate hospital each time it switches (or is used as a control).

variable indicating the year after reclassification is measuring time varying area-specific effects—time varying effects common to all hospitals in this area (this is trivially true since there is only one area). The same basic logic can be expanded to many areas.

What makes equation (3) difficult to estimate is that the degrees of freedom are quickly exhausted. This specification is only feasible if there are a large number of hospitals in each area, which is generally not the case. However, if the unit of analysis is the patient in hospital (i), there are ample degrees of freedom since there are many observations per hospital. Therefore, equation (3) will only be estimated for models where we are examining the effect of Medicare reimbursement on patient outcomes.

Data

Three data sources were used in the analysis: the Prospective Payment System Payment Impact (PPS Impact) files from 1994 to 2001 from the Center for Medicare and Medicaid (CMS), the American Hospital Association Annual Surveys from 1994 to 2001, and the Nationwide Inpatient Sample (NIS) for 1994 to 2001 from the Healthcare Cost and Utilization Project (HCUP) of the Agency for Healthcare Research and Quality (AHRQ).

Our first task was to identify hospitals that were reclassified (or declassified). To accomplish this task, we used the PPS Impact files. These files are maintained by CMS and used to calculate payments under Medicare's PPS. Most importantly, they provide information on the operating wage index, a key determinant of Medicare reimbursement rates, and whether a hospital has been geographically reclassified. The only other information we used from these files was the Medicare case mix index, which measures the average severity of illness. We merged the files from 1994 to 2001 so that we had a complete history of changes in the operating wage index of the hospital between 1994 and 2001. For all hospitals with non-missing observations (99% of sample), we selected those that were reclassified, or declassified, with respect to the operating wage index between 1994 and 2001. We refer to these as “switchers” and each “switcher” contributed three years of data: the year that reclassification (declassification) became effective, and the prior two years. Thus, a hospital that was reclassified in year

t, declassified in year t+1 and reclassified in year t+2 was not included. The reason for this restriction is that hospitals know the outcome of their reclassification petition six months prior to it taking effect. Thus, we thought it prudent to omit (in some analyses) the year prior to reclassification (declassification) because hospitals may have responded to the impending reclassification in that year even though their reimbursement remained unchanged. Note that a declassified hospital had to have been reclassified for at least two years to be included in the sample of “switchers.” For example, a hospital that was reclassified in year t and declassified in year t+2 was included, but a hospital that was reclassified in year t and declassified in year t+1 was not included (this hospital may be in the sample as a reclassified hospital if it had not changed status in years t-2 and t-1). Finally, a hospital could be a “switcher” in more than one period, although relatively few (15%) are in the sample more than once, and each is treated as a separate unit in terms of specifying hospital fixed effects.

We identified approximately 927 “switchers” in the PPS files of which 598 were reclassified and 329 were declassified. For each switching hospital, we selected all other hospitals in the same geographic area of origin, or alternatively in the same geographic area of destination, in the year of the switch (reclassified or declassified). We refer to these as control hospitals. By geographic area of origin, we refer to the Medicare defined geographic area that hospital is actually located within, and the area of destination is the Medicare defined geographic area that was used to set reimbursement after reclassification. Each control hospital contributed three years of data, and to be a control, the hospital had to not have a change in its operating wage index during the period (two years prior to switch and year switch became effective). Control hospitals may be in the sample multiple times. If there were no control hospitals, we dropped the “switcher,” and this left 805 “switchers” with controls chosen on the basis of the originating geographic area, and 905 “switchers” with controls chosen on the basis of the destination area.

The second data source we used was the American Hospital Association Annual Surveys (AHA) from 1994 to 2001. Each year the American Hospital Association has conducted its Annual Survey of hospitals to collect information about the hospital’s organizational structure, personnel, facilities and

services, and financial performance. The response rate is over 80%. We used these data to obtain information about the following for each hospital:

- number of beds in hospital unit and nursing home unit (if present);
- ownership status (non-profit, for-profit);
- teaching status;
- nursing (RN, LPN) resources used in fiscal year, as measured by total facility (hospital and nursing home), full-time equivalents (FTEs);
- physician resources used in fiscal year, as measured by total facility, full-time equivalents (FTEs);
- total inpatient admissions in hospital unit and nursing home unit (if present) in fiscal year;
- inpatient days in hospital unit and nursing home unit (if present) in fiscal year;
- Medicare inpatient days in hospital and nursing home unit (if present) in fiscal year;
- and total number of outpatient visits in fiscal year.

We restricted the sample to private (non-profit or for-profit), short-term general medical and surgical hospitals, and among this group, to hospitals that actually report (no imputation) information for the fiscal year of the survey. Since hospitals use different fiscal year definitions, we defined calendar year as the year with the greatest overlap with the fiscal year. These sample restrictions resulted in approximately 2,900 hospitals per year.

It is important to note that nursing and physician resources refer to the total facility and not just the hospital unit. Since we are interested in the effect of changes in Medicare reimbursement for inpatient and outpatient care on *nursing resources per patient in the hospital unit*, we control in a flexible way (i.e., several dummy variables) for the number of beds, admissions and inpatient days in both the hospital and nursing home units. Our assumption is that the relationship between nursing resource use and the quantity of nursing home beds, admissions and inpatient days is unaffected by changes in Medicare reimbursement for hospital unit care. Given the data there is little else we can do, but it is not obvious why the hospital would change its use of nursing home resources in response to changes in Medicare reimbursement for hospital unit care.

Next, we merged the data from the PPS Impact files to the data from the AHA files. This resulted in the following number of “switchers” and “controls.”

- 342 switchers and 2,870 controls using the geographic area of origin to choose controls;
- and 393 switchers and 2,178 controls using geographic area of destination to choose controls.

These are the samples of hospitals that we use to examine changes in nursing resources in response to a change in Medicare reimbursement. It is important to note that the decrease in the number of “switchers” from that identified solely from the PPS Impact data is driven by the restrictions used to select the sample of hospitals from the AHA data.¹³

The final data source used in the analysis is the Nationwide Inpatient Sample (NIS) for 1994 to 2001. We use these data to obtain information about patient outcomes. The NIS is a public use file containing information on every (admission) discharge from a 20 percent sample of non-federal, short-term, general and other specialty hospitals in a sample of states. The number of states reporting information has grown over time. In 1994, 15 states participated, and in 1999, 19 states participated.¹⁴ While the number of states that have participated in HCUP has grown since 1999, this is the last year that is relevant to our analysis since we require a hospital to be present for three years, and 2001 is the last year of information from our other data sources. The NIS has information about: the age of the patient, state of residence, hospital characteristics (from AHA survey), the principal and secondary diagnoses, principal procedures, length of stay, and inpatient mortality.

We merged the patient discharge records from the NIS to the hospital level data using the AHA identification number. Unfortunately, relatively few “switchers” merge, and as a result the number of “switchers” for which we have patient information is 26 (or 28 if destination area is used to select controls). The primary reasons for this dramatic decrease are the limited number of states that participated in the NIS, and the 20% sample frame used to select hospitals in those states. Specifically, 64% of the switchers are lost because of the limited number of states that participated in NIS, and 27%

¹³ Short-term, general medical and surgical hospitals make up approximately half of the hospitals in the AHA, and missing AHA data further limited the sample.

¹⁴ In 1994, the following states participated: AZ, CA CO, CT, FL, IL, IA, MD, MA, NJ, NY, OR, PA, WA, and WI. In 1999, participating states were: AZ, CA CO, CT, FL, IL, IA, MD, MA, ME, MO, NJ, NY, OR, PA, UT, VA, WA, and WI.

are lost due to the hospital not being present in three consecutive years.¹⁵ There was a corresponding decrease in the number of control hospitals.

For each hospital with patient level information, we limited the sample to patients between the ages of 40 and 80. We also restricted the patient records to those admitted for a limited number of illnesses (primary diagnoses), defined by ICD-9 codes. The purpose of using patient records was to examine outcomes that may be related to changes in hospital resource use due to changes in Medicare reimbursement. Since nursing resources are the largest single source of labor, we focused on outcomes that are particularly sensitive to nursing care (Needleman et al. 2005). These outcomes include urinary tract infections, pressure ulcers, secondary pneumonia, deep vein thrombosis, and failure to rescue. Identification of these outcomes using diagnostic and procedure codes is provided by Needleman et al. (2001). We also use inpatient mortality as an outcome. In addition, we limited the patient sample to those admitted for primary diagnoses for which the incidence of the outcomes of interest was not rare (< 1%). To select these diagnoses, we examined all discharges in the HCUP data for 1998, and calculated the incidence of each outcome by primary diagnosis and ranked the outcomes. Based on this analysis, we selected all admissions for the following primary diagnoses (ICD-9 codes): Septicemia; Volume Depletion; Ischemic Heart Disease; Diseases of Pulmonary Circulation; Other Forms of Heart Disease; Cerebrovascular Disease; Diseases of Arteries, Arterioles, and Capillaries; Diseases of Veins, and Lymphatics, and Other Diseases of the Circulatory System; Pneumonia and Influenza; Pneumoconioses and Other Lung Diseases Due to External Agents; and Other Diseases of the Respiratory System.¹⁶

¹⁵ Prior to 1998, the NIS sample was chosen to preserve a longitudinal component—hospitals previously surveyed had a greater likelihood of being surveyed in the following year. This sampling procedure was discontinued in 1998.

¹⁶ The ICD-9 codes for each of these categories is: Septicemia (all ICD-9 beginning with 038); Volume Depletion (ICD-9 2765); Ischemic Heart Disease (all ICD-9 codes beginning with 410-414); Diseases of Pulmonary Circulation (all ICD-9 codes beginning with 415-417); Other Forms of Heart Disease (all ICD-9 codes beginning with 420-429); Cerebrovascular Disease (all ICD-9 codes beginning with 430-438); Diseases of Arteries, Arterioles, and Capillaries (all ICD-9 codes beginning with 440-448); Diseases of Veins, and Lymphatics, and Other Diseases of the Circulatory System (all ICD-9 codes beginning with 451-459); Pneumonia and Influenza (all ICD-9 codes beginning with 480-487); Pneumoconioses and Other Lung Diseases Due to External Agents (all ICD-9 codes beginning with 500-508); and Other Diseases of the Respiratory System (all ICD-9 codes beginning with 510-519).

Results

Analysis of Hospital Resource Use

Table 1 presents descriptive statistics of hospital-level characteristics, measured two years before reclassification, for the sample of hospitals used in the analysis. Separate statistics are calculated for “switchers” and “controls.” Two sets of figures are shown: one for “switchers” and “controls” when “controls” are chosen from the geographic area of origin; and the other when “controls” are chosen from the geographic area of destination. The number of “switchers” differs in the two samples because we drop “switchers” from areas that do not have any “controls.”

As can be seen in Table 1, “switchers” are larger than hospitals in their area of origin and smaller than hospitals in their area of destination. The average “switcher” has approximately 36 (41%) more beds than other hospitals in their area of origin and 80 (35%) fewer beds than hospitals in their area of destination. “Switchers” also have a higher Medicare Case Mix index than hospitals in their area of origin and a lower Medicare Case Mix index than hospitals in their area of destination. These differences between switchers and controls are consistent with the process of geographical classification, which is mainly a way for rural and urban fringe hospitals with unusually high labor costs to obtain greater reimbursement. So it appears that it is the larger hospitals with sicker patients in rural and urban fringe areas that have the high labor costs. Interestingly, “switchers” use fewer LPN resources per admission than hospitals in the area of origin, but more LPN resources per admission than hospitals in the area of destination. “Switchers” also use fewer RN resources per admission than other hospitals in the area of origin and destination.

Overall, the figures in Table 1 demonstrate that “switchers” are different from other hospitals in both their area of origin and their area of destination. So it is unlikely that simply controlling for area of origin, or area of destination, is sufficient to establish (conditional) exogeneity of “switcher” status. A more plausible approach would be to control for hospital-specific effects. Below, we present results from both approaches.

We begin the analysis by demonstrating that geographic reclassification has a significant effect on the operating wage index. This is not unexpected since geographical reclassification by definition requires a change in the operating wage index of between 6 and 16 percent. And estimates in Table 2 confirm this. Again, two sets of estimates are presented: one for each sample of “switchers” and “controls.” The left panel shows estimates for the sample consisting of hospitals in the origin area and the right panel shows estimates for the sample consisting of hospitals in the destination area. For each sample, estimates from two models are shown: one model controls for area-year fixed effects (column 1) and the other controls for hospital fixed effects and year (column 2). Estimates are obtained from a difference-in-differences regression model that includes the following controls in addition to those listed in the table: treatment (switch=1 if reclassified, 0 otherwise), period (post=1 if after reclassification, 0 otherwise), and interaction between treatment and period. Estimates in Table 2 are the coefficient on the interaction terms. Not surprisingly, estimates show that “switchers” experience a 9 to 12 percentage point change in the Medicare operating wage index relative to controls, which is the equivalent of an approximately 10 percent change in the wage index and therefore 10 percent change in Medicare reimbursement.¹⁷ In Table 2, we also show the change in the operating wage index for controls. These estimates (coefficient on POST in equation (1)) demonstrate that control hospitals experienced little change in the operating wage index.

Table 3 presents regression estimates of the effects of Medicare reimbursement on hospital use of resources. Our preferred estimates are those that hold constant hospital-specific effects, so we limit the discussion to these estimates. Few of the estimates in Table 3 are statistically significant, and most are also small in magnitude. One estimate that is significant indicates that hospitals that were reclassified, and which therefore experienced approximately a 10 percent increase in reimbursement, employed approximately five (4.771) to seven (6.550) fewer nurses, which is a three to four percent decline. Hospitals that were reclassified, and who experienced decreases in Medicare reimbursement of approximately 10 percent, increased the number of nurses by four (3.639) to six (5.637), or two to four

¹⁷ The operating wage index enters the reimbursement formula multiplicatively.

percent, but these estimates are not statistically significant. These estimates related to nursing resources are surprising and inconsistent with theoretical predictions.

The only other statistically significant estimates pertain to inpatient days. When “controls” are selected from the area of destination, geographical reclassification is associated with a statistically significant change in inpatient days. Hospitals that were reclassified experienced a three percent decrease in inpatient days. Similarly, hospitals that were declassified experienced a three percent increase in inpatient days, but this estimate is not statistically significant. Given that reclassification is not associated with a change in admissions, changes inpatient days imply changes in length of stay. On first thought, this may appear to be inconsistent with what theory predicts—increases in reimbursement are predicted to increase quality (intensity) and therefore increase length of stay. But perhaps, the intensity of resource use per day is increased in response to an increase in reimbursement, and this may reduce length of stay. However, some caution is required here, since the estimates were only statistically significant when controls were chosen from destination area, and only for reclassified hospitals.

One prediction of our theoretical model, which is due the assumption of joint production of some inputs (e.g., nurses), was that changes in Medicare reimbursement would have smaller effects the larger the share of Medicare patients. To examine whether this is true, we allowed the effect of interest to differ by the *initial* share of Medicare patients. We calculated the share of Medicare patients in year t-2 and used that share to classify hospitals into three categories: 0-49 percent, 50-69 percent, and 70 or more percent. Tables 4a and 4b present the estimates: Table 4a shows estimates when “controls” were chosen from the geographic area of origin, and Table 4b shows estimates when “controls” were chosen from the geographic area of destination. Again, we focus the discussion on the models that control for hospital-specific fixed effects (other models not shown).

Estimates in Tables 4a and 4b do not, in general, indicate that hospital responses to changes in Medicare reimbursement differed significantly by share of Medicare patients. For example, the negative association between RNs per admission and geographic reclassification observed in Table 3 is also found in Tables 4a and 4b and it does not differ significantly across the three Medicare share categories. It does

appear to be the case that hospitals with the smallest share of Medicaid patients have the largest response to changes in Medicare reimbursement, but estimates are relatively imprecise, so it is difficult to interpret the differences among estimates. Moreover, it is still the case that the response is contrary to theory—greater reimbursement is associated with fewer nurses. Overall, the estimates in Tables 4a and 4b suggest that there is some variation in hospital response to changes in Medicare reimbursement depending on the hospital's share of Medicare patients, but the imprecision of the estimates prevents easy characterization of this variation. Finally, estimates in Tables 4a and 4b are also inconsistent with the model proposed by Glazer and McGuire (2002), which predict larger effects the larger share of Medicare. There is no evidence that this is the case.

In sum, the results to this point show that significant changes in Medicare reimbursement had little effect on hospital resource use as measured by admissions, inpatient days or nurse resources. In fact, increases in Medicare reimbursement associated with geographical reclassification were associated with decreases in nursing resources. This is a surprising finding, and one that contradicts theoretical, or intuitive, expectations. While not large, a 10 percent increase in Medicare reimbursement is associated with approximately a three percent decrease in RN resources.

Analysis of Patient Outcomes

We now turn to the effect of Medicare reimbursement on patient outcomes. As noted, we focus on the effects of Medicare reimbursement on nurse-sensitive patient outcomes. These are outcomes that are considered to be particularly sensitive to changes in nursing resources and include: secondary pneumonia, deep vein thrombosis, failure-to-rescue, pressure ulcers, and urinary tract infections. We chose these outcomes because nurses represent approximately 30 percent of hospital operating budgets and are the largest department in hospitals. Therefore, nurse resources and outcomes sensitive to changes in this resource are likely to be affected by changes in Medicare reimbursement. In addition to these patient outcomes, we examine in-hospital mortality. Previously, we found that increases in Medicare reimbursement are associated with a decrease in nursing resources. This suggests that we may find that

increases in Medicare reimbursement are associated with a worsening of patient outcomes that are sensitive to nursing care. However, this potential consequence may be offset by changes in other resources associated with changes in reimbursement that we have not examined.

Table 5 presents the means of patient outcomes in year (t-2) for “switcher” and “control” hospitals. We divide patients into two groups: those between the ages of 40 and 64, which are predominantly private payer, and those 65 to 80 who are all covered by Medicare. The division of the sample into private (age 40 to 65) and public (age 65 to 80) patients allows us to investigate whether changes in Medicare reimbursement affected private as well as public (i.e. Medicare) patients. With one exception, there are no statistically significant differences in patient outcomes between the two types of hospitals. The lone exception is the rate of failure to rescue among patients aged 65 to 80, which is higher among “control” hospitals in the geographic area of origin.

Estimates of the effect of geographic reclassification on patient outcomes are presented in Table 6. Here, our preferred model is that which controls for hospital-specific effects and area-year effects. We begin the discussion with the results obtained when controls were chosen from area of origin. Patient outcomes in hospitals that were reclassified and which received an increase in reimbursement showed both improvement and deterioration. There was a significant increase (18 percent) in the incidence of pressure ulcers among those 40 to 64, and a significant increase (26 and 36 percent, respectively) in the incidences of pressure ulcers and failure-to-rescue among those 65 to 80. However, there was decrease (33 percent) in the incidence of DVT/PE among those 65 to 80. For patients in hospitals that were declassified, and who received lower Medicare reimbursement, there was an increase (50 and 100 percent, respectively) in mortality and failure-to-rescue among those 40 to 64, and a decrease (25 percent) in pressure ulcers among those 65 to 80.

Estimates in the right panel of Table 6 are obtained using “controls” selected from the area of destination. In hospitals that were reclassified and who received an increase in reimbursement, there was an increase (18 percent) in pressure ulcers among those 40 to 64. In hospitals that were declassified, there was an increase (approximately 30 percent) in the incidences of DVT/PE and failure-to-rescue among

those 40 to 64, and an increase in the incidences of DVT/PE and urinary tract infection among those 65 to 80. However, there was also a decrease (20 percent) in mortality and failure-to-rescue among this group of patients.

Overall estimates in Table 6 provide limited and mixed evidence as to the effect of Medicare reimbursement on patient outcomes. Increases in reimbursement are associated with both better and worse outcomes, and estimates are sensitive to the choice of “controls.”

Conclusions

In this paper, we examined the association between changes in Medicare reimbursement and hospital resource use and patient outcomes. Specifically, we studied the effect of changes in the Medicare operating wage index caused by geographic reclassification on hospital admissions, inpatient days and nursing resources, and on patient outcomes. For patient outcomes, we focused on nurse-sensitive measures—outcomes that are sensitive considered to be to changes in the quantity of nursing care—and in-hospital mortality. Our objective was to obtain estimates of the associations of interest that could plausibly be given a causal interpretation. Accordingly, we used a research design that controlled for unmeasured hospital-specific effects that are correlated with geographic reclassification and the outcomes of interest. And for the patient-level analyses, we included additional controls for unmeasured, time-varying geographic area effects.

Our theoretical model, as well as other similar models in the literature (e.g., Hodgkin and McGuire 1994, Glazer and McGuire 2002), predicts that an increase in Medicare reimbursement would be associated with an increase in hospital admissions of Medicare patients (i.e., quantity), an increase in nursing resources (i.e., quality), and an improvement in patient outcomes. In contrast to these predictions, we found that an increase in Medicare reimbursement was associated with a decrease in nursing resources; a 10 percent increase in the Medicare operating wage index is associated with a three percent decrease in RN resources. Our model also suggested that any effects of changes in Medicare

reimbursement will likely differ by the importance of Medicare to hospital revenues. However, we found no evidence to support this assumption.

Estimates of the association between changes in Medicare reimbursement and patient outcomes were mixed. Changes in reimbursement were associated with both better and worse outcomes. Moreover, the association between changes in Medicare reimbursement and patient outcomes was not consistent with the association between changes in reimbursement and nursing resources. Increases in reimbursement were associated with a decrease in nursing resources, but increases in reimbursement were not consistently associated with an increase in adverse events particularly associated with nursing care.

It is difficult to draw conclusions from this analysis. Increases in Medicare reimbursement appear to be associated with decreases in nursing resources. This was a relatively robust finding from what we believe is a strong research design. But it is inconsistent with most predictions. The purpose of geographical reclassification is to provide a hospital with additional resources to pay for labor costs that are higher than average. Therefore, it is difficult to understand why a hospital that receives such resources would employ fewer nurses. Obviously, some limitations of the study may partly explain the results. Our measure of nursing resources comes from the American Hospital Association Annual Surveys and is a crude measure that may contain significant measurement error. We also had a selected sample of hospitals—those that were geographically reclassified for reimbursement purposes—and as shown above these hospitals are larger and serve sicker patients than other hospitals in their area, but are smaller and have less sick patients than hospitals in the reclassified area. Moreover, because of data limitations, we had very few hospitals in the patient level analyses. So our findings, if valid, may still not be applicable to a large portion of hospitals.

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Table 1
Differences in Characteristics Between Hospitals Reclassified and Hospitals Not Reclassified
Two Years Prior to Reclassification

Variable	Controls Chosen From Originating Area				Controls Chosen From Destination Area			
	Switchers	Controls	Dif.	Adj. Dif.	Switchers	Controls	Dif.	Adj. Dif.
<i>Hospital Unit</i>								
Beds	132.2	87.92	44.28	36.46*	150.3	226.0	-75.70	-80.19*
Admissions / 1000	5.495	3.373	2.122	1.670*	6.289	9.662	-3.373	-3.501*
Inpatient Days / 1000	26.24	16.58	9.660	7.412*	30.81	52.30	-21.49	-21.26*
Medicare Share of Inpatient Days	0.573	0.594	-0.021	-0.010	0.561	0.529	0.032	0.035*
Medicare Case Mix	1.246	1.156	0.090	0.079*	1.270	1.364	-0.094	-0.117*
<i>Total Facility</i>								
Beds	148.8	107.4	41.40	36.08*	165.5	243.8	-78.30	-83.17*
Admissions / 1000	5.617	3.444	2.173	1.720*	6.404	9.840	-3.436	-3.573*
Inpatient Days / 1000	31.72	22.98	8.740	7.381*	35.76	57.69	-21.93	-21.84*
Medicare Share of Inpatient Days	0.545	0.498	0.047	0.035*	0.540	0.517	0.023	0.025*
RN	149.2	95.02	54.18	45.59*	171.98	290.1	-118.1	-120.8*
RN / (Tot Fac Admissions / 1000)	27.41	29.29	-1.880	-1.250*	27.51	29.03	-1.520	-1.420*
LPN	30.88	21.24	9.640	8.247*	31.15	32.22	-1.070	-6.399*
LPN/(Tot Fac Admissions/1000)	7.089	9.324	-2.235	-2.176*	6.469	4.714	1.755	1.442*
PHY	7.564	7.122	0.442	1.771	8.883	25.00	-16.12	-11.95*
PHY/(Tot Fac Admissions/1000)	1.582	1.616	-0.034	0.102	1.471	1.716	-0.245	-0.125
For Profit	0.184	0.099	0.085	0.068*	0.178	0.130	0.048	0.022
Teaching	0.029	0.020	0.009	0.011	0.041	0.124	-0.083	-0.051*
High Technology	0.216	0.115	0.101	0.099*	0.264	0.444	-0.180	-0.209*
Observations	342	2870			393	2178		

Notes:

1. Switchers are hospitals that changed geographic location with respect to assignment of operating wage index used to compute Medicare reimbursement. Controls are those that did not change geographic location with respect to operating wage index used to compute Medicare reimbursement.
2. Adjusted differences control for area-year effects. In other words, adjusted differences between switchers and controls pertain to hospitals in the same area, defined prior to reclassification, and year.
3. * indicates statistically significant difference ($p < 0.05$); standard error of difference was calculated under the assumption that observations were not independent within year and geographic area.
4. Medicare inpatient share is missing in a few cases. Origin area observations: 321 switchers, 2712 controls; destination area N: 372 switchers, 2067 controls.

Table 2
 Estimates of the Effect of Geographical Reclassification on Medicare Operating Wage Index
 Change in Operating Wage Index Pre- and Post-Reclassification

Variable	Controls Chosen From Originating Area		Controls Chosen From Destination Area	
	Switchers – Reclassifiers (relative to controls)	0.094* (0.006)	0.093* (0.006)	0.105* (0.007)
Switchers – Declassifiers (relative to controls)	-0.126* (0.008)	-0.123* (0.007)	-0.101* (0.010)	-0.095* (0.008)
Controls	-0.003* (0.001)	0.009* (0.002)	-0.001 (0.001)	0.007* (0.002)
Area-Year Fixed Effects	Yes	No	Yes	No
Hospital Fixed Effects	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes
Observations	6424		5142	
Number of Hospitals	3212		2571	

Notes:

1. Reclassifiers are hospitals that switched from their original geographic location with respect to assignment of operating wage index used to compute Medicare reimbursement to another geographic location. Declassifiers are hospitals that were reclassified back to their original geographic location.
2. All regressions control for Medicare case mix and for teaching, hi-tech, for-profit status, reclassifier (declassifier) status, and reclassifier-status and declassifier-status interacted with post-period.
3. * indicates a statistically significant difference ($p < 0.05$); + indicates a statistically significant difference ($0.05 \leq p < 0.10$); standard errors were calculated under the assumption that observations were not independent within year and geographic area.
4. Estimates pertain to periods (t-2) and (t), where t is the year of reclassification.

Table 3
Estimates of the Effect of Geographical Reclassification on Hospital Characteristics

Variable	Controls Chosen From Originating Area				Controls Chosen From Destination Area			
	Reclassifier	Declassifier	Reclassifier	Declassifier	Reclassifier	Declassifier	Reclassifier	Declassifier
<i>Hospital Unit</i>								
Admissions / 1000	-0.072 (0.305)	0.120 (0.625)	0.020 (0.070)	0.176 (0.122)	-0.020 (0.527)	0.269 (0.735)	-0.194 (0.115)	-0.034 (0.130)
Inpatient Days / 1000	-0.770 (1.521)	0.396 (2.418)	-0.218 (0.364)	0.533 (0.759)	-0.056 (2.401)	1.987 (3.321)	-0.807+ (0.461)	0.875 (0.772)
Medicare Share of Inpatient Days	0.001 (0.013)	0.007 (0.015)	-0.001 (0.008)	0.012 (0.010)	0.009 (0.012)	-0.011 (0.025)	-0.003 (0.008)	-0.0002 (0.009)
<i>Total Facility</i>								
RN	-3.801 (5.409)	-5.154 (10.51)	-4.771+ (2.793)	3.639 (3.692)	-0.568 (8.175)	9.606 (10.81)	-6.550+ (3.572)	5.637 (4.915)
LPN	-1.320 (1.593)	-1.530 (2.263)	-0.771 (0.851)	-1.227 (1.028)	0.418 (2.901)	0.237 (4.227)	0.358 (1.002)	-0.080 (1.073)
Area-Year Fixed Effects	Yes		No		Yes		No	
Hospital Fixed Effects	No		Yes		No		Yes	
Year Fixed Effects	No		Yes		No		Yes	
Observations	6424		6424		5142		5142	
Number of Hospitals	3212		3212		2571		2571	

Notes:

1. All regressions control for Medicare case mix and for teaching, hi-tech and for-profit status. In addition, the RN and LPN regressions also control for hospital unit and nursing unit beds, admissions and inpatient days; and outpatient and missing outpatient visits.
2. * indicates a statistically significant difference ($p < 0.05$); + indicates a statistically significant difference ($0.05 \leq p < 0.10$); standard errors were calculated under the assumption that observations were not independent within year and geographic area.
3. Estimates pertain to periods (t-2) and (t), where t is the year of reclassification.
4. In the originating area, Medicare share has only 6095 observations for 3186 hospitals, 277 of which have missing Medicare share in one of the periods. In the destination area, Medicare share has only 4904 observations for 2546 hospitals, 188 of which have missing Medicare share in one of the periods.

Table 4a
 Estimates of the Effect of Geographical Reclassification on Hospital Characteristics
 By Medicare Share of Inpatient Days – Controls Chosen from Originating Area

Variable	Medicare Share 0-49% Reclassifier	Medicare Share 50-69% Reclassifier	Medicare Share ≥70% Reclassifier	Medicare Share 0-49% Declassifier	Medicare Share 50-69% Declassifier	Medicare Share ≥70% Declassifier
<i>Hospital Unit</i>						
Admissions / 1000	-0.337 (0.286)	0.044 (0.044)	-0.061 (0.057)	0.412 (0.412)	0.149* (0.069)	-0.152 (0.107)
Inpatient Days / 1000	-1.674 (1.355)	-0.119 (0.345)	-0.240 (0.404)	-0.895 (1.184)	0.306 (0.539)	1.108 (2.169)
<i>Total Facility</i>						
RN	-11.35 (9.086)	-4.104 (2.612)	-1.329 (4.910)	6.247 (10.85)	-0.389 (3.775)	10.17+ (5.374)
LPN	0.373 (2.003)	-0.660 (1.062)	-1.746 (1.382)	-2.485 (1.786)	-1.463 (1.301)	-0.661 (2.980)
Area-Year Fixed Effects		No			No	
Hospital Fixed Effects		Yes			Yes	
Year Fixed Effects		Yes			Yes	
Observations		6424			6424	
Number of Hospitals		3212			3212	

Notes:

1. All regressions control for Medicare case mix, and for teaching, hi-tech and for-profit status. In addition, the RN and LPN regressions also control for hospital unit and nursing unit beds, admissions and inpatient days; and outpatient and missing outpatient visits.
2. Medicare share refers to the share of hospital unit inpatient days attributable to Medicare.
3. * indicates a statistically significant difference ($p < 0.05$); + indicates a statistically significant difference ($0.05 \leq p < 0.10$); standard errors were calculated under the assumption that observations were not independent within year and geographic area.
4. All estimates pertain to periods (t-2) and (t), where t is the year of reclassification.
5. Medicare share has only 6095 observations on 3186 hospitals, 277 of which have missing share in one of the periods.

Table 4b
Estimates of the Effect of Geographical Reclassification on Hospital Characteristics
By Medicare Share of Inpatient Days – Controls Chosen from Destination Area

Variable	Medicare Share 0-49% Reclassifier	Medicare Share 50-69% Reclassifier	Medicare Share ≥70% Reclassifier	Medicare Share 0-49% Declassifier	Medicare Share 50-69% Declassifier	Medicare Share ≥70% Declassifier
<i>Hospital Unit</i>						
Admissions / 1000	-0.603* (0.278)	-0.100 (0.149)	-0.383* (0.136)	0.143 (0.258)	-0.003 (0.165)	-0.429* (0.130)
Inpatient Days / 1000	-2.050 (1.323)	-0.648 (0.442)	-0.817 (0.645)	0.480 (1.245)	1.167 (0.760)	-0.226 (2.101)
<i>Total Facility</i>						
RN	-9.064 (9.636)	-5.162 (3.906)	-5.525 (4.780)	16.43+ (9.248)	0.649 (5.608)	6.041 (5.814)
LPN	1.334 (2.176)	0.515 (1.246)	-0.751 (1.418)	0.558 (1.278)	-0.139 (1.319)	-1.096 (3.037)
Area-Year Fixed Effects		No			No	
Hospital Fixed Effects		Yes			Yes	
Year Fixed Effects		Yes			Yes	
Observations		5142			5142	
Number of Hospitals		2571			2571	

Notes:

1. All regressions control for Medicare casemix, and for teaching, hi-tech and for-profit status. In addition, the RN and LPN also control for hospital unit and nursing unit beds, admissions and inpatient days; and outpatient and missing outpatient visits.
2. Medicare share refers to the share of hospital unit inpatient days attributable to Medicare.
3. * indicates a statistically significant difference ($p < 0.05$); + indicates a statistically significant difference ($0.05 \leq p < 0.10$); standard errors were calculated under the assumption that observations were not independent within year and geographic area.
4. All estimates pertain to periods (t-2) and (t), where t is the year of reclassification.
5. Medicare share has only 4904 observations on 2546 hospitals, 188 of which have missing share in one of the periods.

Table 5
Differences in Patient Outcomes Between Hospitals Reclassified and Hospitals Not Reclassified
Two Years Prior to Reclassification

Variable	Controls Chosen From Originating Area				Controls Chosen From Destination Area			
	Switchers	Controls	Dif.	Adj. Dif.	Switchers	Controls	Dif.	Adj. Dif.
Ages 40-64								
Mortality	0.030	0.031	-0.001	-0.001	0.034	0.037	-0.003	-0.006
Pneumonia	0.025	0.021	0.004	0.005	0.033	0.036	-0.003	-0.003
DVT/PE	0.007	0.009	-0.002	-0.001	0.008	0.011	-0.003	-0.001
Failure to Rescue	0.109	0.104	0.005	-0.000	0.114	0.124	-0.006	-0.021
Urinary Tract Infection	0.042	0.044	-0.002	-0.003	0.040	0.045	-0.005	-0.004
Pressure Ulcers	0.017	0.015	0.002	-0.000	0.015	0.021	-0.006	-0.007
Observations	8828	15960			13963	48766		
Number of Hospitals	26	94			26	65		
Ages 65-80								
Mortality	0.052	0.058	-0.006	-0.006	0.060	0.066	-0.006	-0.005
Pneumonia	0.035	0.033	0.002	0.005	0.038	0.048	-0.010	-0.009
DVT/PE	0.006	0.008	-0.002	-0.001	0.008	0.011	-0.003	-0.001
Failure to Rescue	0.119	0.171	-0.052	-0.050*	0.150	0.173	-0.023	-0.014
Urinary Tract Infection	0.080	0.076	0.004	0.003	0.073	0.087	-0.014	-0.012
Pressure Ulcers	0.019	0.020	-0.001	-0.001	0.022	0.030	-0.008	-0.009
Observations	17135	32799			24664	78388		
Number of Hospitals	26	94			26	65		

Notes:

1. Switchers are hospitals that changed geographic location with respect to assignment of operating wage index used to compute Medicare reimbursement. Controls are those that did not change geographic location with respect to operating wage index used to compute Medicare reimbursement.
2. Adjusted differences control for area-year effects. In other words, differences between switchers and controls pertain to hospitals in the same area, defined prior to reclassification, and year.
3. * indicates a statistically significant difference ($p < 0.05$); standard error of difference was calculated under the assumption that observations were not independent within year and geographic area.
4. The failure-to-rescue outcome has 6% of the observations of the other outcomes because its risk pool is smaller than it is for the rest of the outcomes.

Table 6
Estimates of the Effect of Geographical Reclassification on Patient Outcomes

Variable	Controls Chosen From Originating Area			Controls Chosen From Destination Area		
	Reclassifier	Declassifier	(N)	Reclassifier	Declassifier	(N)
<i>Ages 40-64</i>						
Mortality	-0.001 (0.003)	0.015* (0.005)	50713	0.001 (0.003)	-0.003 (0.002)	131095
Pneumonia	-0.004 (0.003)	-0.000 (0.006)	50730	0.002 (0.003)	-0.004 (0.006)	131098
DVT/PE	-0.000 (0.001)	-0.003 (0.003)	50730	0.0006 (0.009)	0.002* (0.001)	131098
Failure to Rescue	-0.009 (0.037)	0.090* (0.021)	2668	-0.022 (0.023)	0.032+ (0.019)	8654
Urinary Tract Infection	0.005 (0.005)	-0.009 (0.006)	50730	-0.0004 (0.003)	-0.003 (0.004)	131098
Pressure Ulcers	0.003+ (0.002)	0.005 (0.003)	50730	0.003* (0.002)	-0.001 (0.001)	131098
<i>Ages 65-80</i>						
Mortality	0.003 (0.004)	0.013 (0.009)	101457	0.002 (0.003)	-0.012* (0.001)	213271
Pneumonia	0.0003 (0.004)	0.008 (0.005)	101511	0.002 (0.002)	-0.003 (0.004)	213269
DVT/PE	-0.002* (0.001)	0.002 (0.002)	101511	0.0002 (0.001)	0.002* (0.001)	213269
Failure to Rescue	0.044* (0.018)	-0.017 (0.047)	7193	-0.021 (0.022)	-0.052* (0.022)	17971
Urinary Tract Infection	-0.003 (0.006)	-0.004 (0.009)	101511	0.005 (0.005)	0.008+ (0.004)	213269
Pressure Ulcers	0.005* (0.001)	-0.004+ (0.002)	101511	0.002 (0.002)	-0.0003 (0.002)	213269
Area-Year Fixed Effects	Yes	Yes		Yes	Yes	
Hospital Fixed Effects	Yes	Yes		Yes	Yes	
Year Fixed Effects	No	No		No	No	
Number of Hospitals		120			91	

Notes:

1. All regressions control for teaching, profit and hi-tech status, Medicare case mix index and ICD-9-CM codes at the three-digit level, of which there are 67 in the ages 40-64, originating area; 69 in the ages 40-64, destination area; 71 in the ages 65-80, originating area; and 69 in the ages 65-80, destination area.
2. * indicates statistically significant difference ($p < 0.05$); + indicates a statistically significant difference ($0.05 < p < 0.10$); standard errors were calculated under the assumption that observations were not independent within year and geographic area.
3. All estimates pertain to periods (t-2) and (t), where t is the year of reclassification.