IDENTIFYING THE HEALTH PRODUCTION FUNCTION: THE CASE OF HOSPITALS

John A. Romley*,
University of Southern California

Neeraj Sood,
University of Southern California and National Bureau of Economic Research

April 22, 2013

Abstract

Estimates of the returns to medical care may reflect not only the efficacy of more intensive care, but also unmeasured differences in patient severity and the productivity of health-care providers across markets. We use several instruments that are plausibly orthogonal to heterogeneity among producers, as well as patients. We analyze area-level care intensity areas and 30-day survival among Medicare patients treated for heart attack, congestive heart failure and pneumonia. We find that the intensity of care is endogenous for two out of three conditions analyzed, even when focusing on patients for whom unobserved-to-the-researcher heterogeneity in health status is plausibly limited (out-of-state patients admitted on an emergency basis.) Specifically, the elasticity of 30-day mortality with respect to care intensity increases in magnitude from -0.32 to -1.17 for pneumonia and from -0.20 to -0.58 for congestive heart failure, when instrumental variables are used. This finding is consistent with the hypotheses that care intensity at hospitals increases with patient severity, and/or decreases with hospital productivity.

*Email: romley@healthpolicy.usc.edu. We are grateful to seminar participants at Cal State Long Beach, RAND, Rice University, UC Riverside, and University of Houston, and to Jonathan Skinner for helpful comments. Any remaining errors are our own. Raj Mehta and Zachary Wagner-Rubin provided excellent research assistance. We are indebted to the Agency for Healthcare Research and Quality (5R01-HS01854103) for financial support.

1. Introduction

Understanding the marginal product of medical care is critical to ongoing debates about the cost, quality and value of U.S. health care. An array of studies, based on the Dartmouth Atlas of Health Care, find that U.S. regions that spend more on all aspects of medical care have similar or poorer patient outcomes than areas that spend less on medical care (Skinner)(). This evidence has suggested, at least to some observers, that we can reduce medical spending without adversely affecting patient outcomes (Fisher, Wennberg et al. 2003). In contrast, recent studies of hospital care in both the health economics and clinical literatures have found that greater resource use or spending is associated with lower risk-adjusted mortality (Doyle 2005; Chandra and Staiger 2007; Card, Dobkin et al. 2009; Ong, Mangione et al. 2009; Almond, Doyle et al. 2010; Barnato, Chang et al. 2010; Kaestner and Silber 2010; Silber, Kaestner et al. 2010; Doyle 2011; Romley, Jena et al. 2011).

These studies that find positive returns to medical spending have typically focused their attention on the problem of unobserved patient heterogeneity. Health or severity of illness is notoriously difficult for researchers to measure precisely, and patients or providers almost certainly observe more about health or severity of illness than a researcher does. The resulting identification problem is that the intensity of medical care is confounded with unobserved (to the researcher) health status or severity of illness. Typically, the view is that sicker patients receive more intensive care, and so the returns to medical care are biased downward. Thus correcting or accounting for patient selection can increase the estimated returns to medical spending.

One approach to dealing with this patient selection problem is to exploit discontinuities in the intensity of care (Doyle 2005; Card, Dobkin et al. 2009; Almond, Doyle et al. 2010). While this approach is compelling, its generality might be limited. Another approach is to focus on a group of patients for whom the selection problem is plausibly mild, for example, hospitalizations of out-of-state visitors for cardiac emergencies (Doyle 2011). Still another approach exploits the fact that consumers typically prefer to receive health care close to their homes, and uses distance to providers as an exogenous source of variation in intensity (McClellan, McNeil et al. 1994;

Gowrisankaran and Town 1999; Geweke, Gowrisankaran et al. 2003; Chandra and Staiger 2007).

Despite the merit of these approaches, there may be residual heterogeneity with respect to patients, and, importantly, these approaches do not explicitly address the issue of provider heterogeneity. To see this more clearly, consider a scenario where we could randomly assign patients to high-spending versus low-spending hospitals. The random assignment of patients to hospitals implies that patient heterogeneity, whether observed or unobserved, is not a concern. However, estimates of the returns to medical spending might still be biased if high-spending hospitals differ from low-spending hospitals in other respects. For example, high-spending hospitals might have more or less effective management practices, or differential expertise in using cost-saving or quality enhancing technologies. Such hospital characteristics are hard to measure but can be positively or negatively correlated with medical spending, and thus bias estimates of the returns to higher spending.

(Chandra 2013) provides a cogent discussion of this identification problem that even with perfect risk adjustment comparisons across regions of medical spending and outcomes are not informative for answering the question of whether we can reduce spending without affecting patient outcomes. He states that "*Different delivery systems and HRRs vary in expertise, and consequently, the ability to transform measured inputs like hospital days, hospital spending, imaging and specialists' visits into outputs. The variations literature has over stated the benefits to medical spending if measured inputs and expertise are positively correlated (as they will be if they are complements), and understated the value of spending if spending more (i.e. using more hospitals days or physician visits) is a substitute for low expertise*."

This threat to the identification of the production function has also long been a matter of serious concern in applied microeconomics (Marschak and Andrews Jr 1944; Griliches and Mairesse 1998). It might be particularly salient in health care where past research has documented significant variation in expertise or productivity across hospitals or regions

(Skinner, Staiger et al. ; Chandra and Staiger ; Doyle, Ewer et al. 2010; Chandra 2013). What is needed to identify returns to medical spending is variation in spending that is orthogonal to unmeasured patient *and* provider heterogeneity.

In this paper, we estimate the returns to medical spending for hospital care. In particular, we estimate the effect of intensity of hospital care on thirty-day survival among Medicare beneficiaries admitted to a hospital on an emergency basis for heart attack, congestive heart failure, and pneumonia. Coronary care (particularly heart-attack care) has been widely studied (McClellan, McNeil et al. ; Picone, Sloan et al. 2003; Skinner and Staiger 2009; Doyle 2011), while pneumonia is a leading cause of hospital admissions and elderly mortality. Moreover, measures of patient mortality risk and hospital processes of care are available for each of these conditions.

To deal with unobserved patient and production heterogeneity, we appeal to theories of hospital behavior to identify instruments for care intensity. These instruments include insurer concentration, corporate tax rates, wage rates, and market size. We argue below that area hospital intensity should decrease with insurer concentration, corporate tax rates, and wages, but increase with market size.

Motivated by (Doyle 2011), we distinguish between in-state and out-of-state patients, because the problem of patient selection should be mild for out-of-state visitors. In ordinary least squares regressions, we find that the marginal product of the intensity of hospital care within areas is positive, resulting in greater survival for in-state as well as out-of-state patients. Consistent with (Doyle 2011)'s finding, the estimated effect size is significantly larger for out-of-state patients in the case of heart attacks.

We find that our instruments are strongly related to the intensity of hospital care. When we instrument for hospital intensity, we can reject the exogeneity of hospital intensity for out-of-state patients admitted with congestive heart failure or pneumonia. The elasticity of thirty-day survival with respect to hospital intensity increases in magnitude from 0.32 (OLS) to 1.17 (IV) for pneumonia, and from 0.20 (OLS) to 0.58 (IV) for congestive heart failure.

Altogether, our findings indicate that there is substantial unobserved heterogeneity confounding the intensity-mortality relationship for pneumonia and congestive heart failure, even among populations for whom the patient selection problem is relatively mild. The downward bias in the returns to hospital care under OLS is consistent with the hypotheses that care intensity increases with unobserved patient severity, and/or decreases with productivity. This finding is also consistent with results from (Chandra 2013) who finds that, in the case of reperfusion therapy, hospitals that provide this treatment to a larger fraction of patients have lower benefits from treatment conditional on patient characteristics.

Our finding that the returns to medical care are positive implies that it is likely that overall reductions in hospital spending will have adverse effects on patient outcomes. However, our findings do not imply that there is no "wasteful" spending in the US health care system. It is certainly possible that there are large inefficiencies within hospitals or within regions (Chandra 2013). As a corollary, the returns to medical spending are context specific. They might be influenced by where and how spending is reduced. For example, policies that aim to reduce spending by penalizing hospital readmissions might produce different outcomes than policies that aim to reduce spending by across the board cuts in hospital reimbursement. Our estimates capture the returns to variation in spending across regions that result from variation in our instruments. Thus, our estimates are most applicable to measuring the impact on medical spending and patient outcomes of policy changes that affect insurer market concentration or hospital reimbursement, market size or number of patients seeking hospital care, tax rates, and hospital input prices.

The remainder of this paper is organized as follows: In Section 2, we review the threats to identification of the health production function and present our identification strategy for the case of hospitals. In section 3, we implement and assess our identification strategy with an analysis of intensity of care and thirty-day mortality for Medicare patients hospitalized for a variety of conditions. Section 4 concludes.

2. Identification Problems and Identification Strategy

2.1 Identification Problem

We consider the following production function for a health outcome:

$$\bar{H} \equiv E\left(H \middle| I, \mathbf{S}, s, A, a\right) = f(I, \mathbf{S}, s, A, a), \tag{1}$$

in which H is health (the output), and $\bar{H}$ is its conditional expectation. Health is determined by the intensity of health inputs, measured by the index I. We abstract from issues of input aggregation, following the relevant literature (Fisher, Wennberg et al. 2003; Doyle 2011). Health is further determined by the initial severity of illness $\boldsymbol{S}$, a vector observed by the researcher. Unobserved health status is measured by s, while A and a measure observed and unobserved provider heterogeneity.

Our goal is to consistently estimate the health production function f, which is assumed known up to a parameter vector. The marginal product of intensity f_I is of particular interest, due to its importance to debates about the social value of health care.

There are two fundamental threats to the identification of the health production function. These threats arise from the sources of unobserved heterogeneity in the production function of equation (1). Loosely speaking, there are distinct threats from the consumers of health and from the producers of health. The reason is that the output of health is produced jointly by consumers as well as producers.

The consumer threat is that severity of illness determines the intensity of care. For example, sicker people require, and are likely to receive, more intensive care. Insofar as severity is unobserved, the marginal product of intensity will tend to be understated.

The top panel of Figure 1 explores the implications of patient heterogeneity. Consider an increase in intensity from point A to point B. If the researcher observed severity perfectly (and there were no productivity differences), she could normalize each hospital's production function so that variation in intensity traced out variation in health outcomes along a common production frontier. In reality, a researcher almost certainly cannot observe severity perfectly. Absent an effective strategy for dealing with patient heterogeneity, a researcher is effectively comparing intensity and health levels across multiple production functions differentiated by patient severity. The lower production function in the figure corresponds to a hospital with higher unobserved severity. If this hospital delivered more intensive care, a naïve comparison of points A and B would understate the marginal product of care intensity.

This sample selection problem, commonly referred to as *patient selection*, has been a central concern of prior studies of the returns to health care. One group of studies employs regression-discontinuity designs that exploit clear breaks in intensity that are plausibly unrelated to severity. For example, (Almond, Doyle et al. 2010) analyze treatment intensity and mortality among newborns just above and just below the threshold for very low birth weight. (Card, Dobkin et al. 2009) compare hospital intensity and mortality among patients with non-deferrable conditions who are just under the age of 65 to similar patients who are just over 65, and thus categorically eligible for Medicare coverage. Both studies find that higher intensity is associated with significantly lower mortality. While this evidence is compelling, regression-discontinuity designs can be applied only in a limited range of settings, and their results may not generalize to other settings.

Other studies focus on groups of patients who are arguably homogeneous. For example, (Doyle 2005) analyzes patients involved in automobile accidents, because medical care for these serious events is typically not discretionary. Patients with health insurance received more intensive treatment, and were substantially more likely to survive their accidents. (Doyle 2011) investigates hospital patients admitted for heart-related emergencies, with a particular on out-of-state visitors. The rationale is that heart-related emergency admissions represent serious health shocks for which patients have limited discretion in selecting hospitals [(Card, Dobkin et al. 2009) also focuses on emergency hospitalizations]. Out-of-state visitors are a small share of patients, and are therefore unlikely to affect the intensity decisions of hospitals. (Fisher, Wennberg et al. 2003) measure spending among decedents, on the grounds that illness severity is homogeneous within this population, while intensity for decedents is correlated with intensity among all patients.

Still other studies instrument for the intensity of hospital care. For example, (McClellan, McNeil et al.) instrumented for the use of specific advanced cardiac services (catheterization and revascularization) over the period 1987-1991, based on the distance between a patient and the nearest hospital with these capabilities, relative to the distance to the nearest hospital. (Picone, Sloan et al.) analyzed mortality for patients with coronary heart disease, congestive heart failure, stroke and hip fracture, instrumenting for the cost of the index admission with area-level measures of labor costs and market competiveness.

The producer threat to identification is that producer heterogeneity may also determine the intensity of care. For example, poorly managed hospitals might have higher spending per patient and poorer health outcomes. In this case unobserved differences in management or governance among providers would lead to a downward bias in estimates of returns to medical spending. Alternatively, hospitals that can achieve good outcomes for a given level of spending may tend to spend more (Marschak and Andrews Jr ; Griliches and Mairesse); if so, the returns to medical spending can be overstated. Evidence of productivity differences within the health-care sector is compelling (Skinner, Staiger et al. 2006; Chandra and Staiger 2007; Weinstein and Skinner ; Chandra 2013).

(Skinner and Staiger 2009) analyze the adoption by hospitals of highly effective, often low-cost innovations in heart-attack treatment over 1986-2004, in particular, beta blockers, aspirin use, and primary reperfusion. Adoption of these technologies represented an upward shift in production functions, because the same intensity of use of labor and capital inputs delivers better survival. The fastest adopters of the new technologies achieved 1-year heart-attack survival rates that were 3.3 percentage points higher than the rates achieved by the slowest adopters. This difference corresponds to nearly one-third of the overall improvement in outcomes during the period studied.

The bottom panel of Figure 1 explores the implications of production heterogeneity for estimates of the returns to hospital care. Absent an effective strategy for dealing with production heterogeneity, a researcher compares multiple production functions differentiated by productivity. The higher production function corresponds to a hospital with higher productivity. If this hospital delivered more intensive care, a naïve comparison of points A and B would overstate the marginal product of care intensity. The figure as drawn is consistent with the notion that more intensive hospitals are also more likely to adopt productivity-enhancing (that is, effective and low-cost) innovations for improving patient survival. The threat to identification from such producer differences in adoption of such technologies — or other sources of provider heterogeneity — has received less attention than patient selection in the literature on the returns to health care.

Strategies which are effective in dealing with patient heterogeneity need not be effective in dealing with production heterogeneity. For example, while out-of-state patients admitted to hospitals for heart-related emergencies are plausibly homogeneous in terms of severity, their hospitals may nevertheless differ in their productivity, resulting in systematic and confounded differences in care intensity.

Outside of health economics, a number of strategies for dealing the identification threat from unobserved productivity have been pursued, including dynamic panel models and control functions (Arellano and Bond 1991; Olley and Pakes 1996). Our strategy for identifying the hospital production function identifies instruments for care intensity from theories of hospital behavior, as we discuss below.

2.2 Identification strategy

Our strategy is to appeal to a standard model of hospital behavior to identify instruments for the intensity of hospital care *I* in the health production function of equation (1) (Hodgkin and McGuire 1994). In this model hospitals maximize utility which is a function of variable profits as well as the intensity of care. The inclusion of intensity of care in the utility function is justified on the grounds that altruistic hospitals might care about the quality of care or health benefits enjoyed by patients. Hospitals face fixed prices as is the case for Medicare. At the margin hospital choose intensity such that the marginal utility of intensity equals the marginal utility of variable profits times the marginal effect of intensity on profits. The marginal effect of intensity on profits can be decomposed into two effects. First, increases in intensity reduce variable profits as the cost of care increases, while prices are fixed. Second, increases in intensity increase variable profits as higher intensity attracts more patients to the provider. Intensity essentially serves as a signal of hospital quality and thus increase demand for the hospital.

Given this model, we posit several plausible instruments for intensity of care. First, higher input prices increase the costs of increasing intensity. Second, greater insurer market power will reduce hospital profit margins and thus reduce returns to attracting new patients by increasing intensity. Similarly, higher corporate tax rates reduce the profits of for-profit hospitals from attracting new patients, and other hospitals may follow for-profit hospitals in reducing intensity. Finally, the market size of a hospital is also a plausible instrument for the intensity of its care. There may be economies of scale in treatment intensity, potentially arising from costs of greater intensity that are fixed with respect to the number of patients treated. If so, fixed costs can be spread across more patients in larger markets, increasing the return to intensity. This reasoning is quite similar to theories of the “medical arms races” among hospitals.(Robinson and Luft) Moreover, a market-size instrument has an analogue in models of pharmaceutical innovation, in which firms have greater incentive to invest in R&D for newer and better drugs in therapeutic areas with greater demand (Finkelstein ; Acemoglu and Linn).

To be valid, our instrument must satisfy two properties. First, they should be correlated with intensity of care. Second, it should be uncorrelated with unobserved patient and hospital level determinants of 30-day survival. We present details of the empirical tests of the validity of our instruments in the next section. To summarize, we show that the instruments are highly correlated with intensity of care. We also perform over identification tests to check the validity of our multiple instruments. In addition, we focus on urban areas and use state-of-the-art controls for patient health status and hospital practices, to limit the possibility that our instruments might be correlated with unobserved heterogeneity in patient survival. Finally, we show that even if our instruments were correlated with unobserved determinants of survival, the relationship between our instruments and unmeasured determinants of survival would have to be much stronger than the relationship with measured factors, in order to negate our findings.

3. Empirical Analysis

In this section we first present our empirical framework. We then describe our analyses of hospital intensity and survival and their results. Initially we deal with unobserved patient heterogeneity by focusing on patients for whom the selection problem should be relatively mild. We then address any remaining patient and production heterogeneity by instrumenting for hospital intensity.

3.1 Empirical framework

We analyze intensity of care and thirty-day survival among elderly Medicare fee-for-service beneficiaries admitted to the hospital with a principal diagnosis of heart attack (acute myocardial infarction), congestive heart failure, and pneumonia. For each of these medical conditions, risk-adjusted mortality is an Inpatient Quality Indicator (IQI) developed and approved by the Agency for Healthcare Research and Quality (AHRQ) for the purpose of assessing hospital quality (Agency for Healthcare Quality and Research). These conditions were also among the most common diagnoses for emergency hospital admissions in (Doyle 2011). We analyze patients admitted on an emergency basis (Doyle 2011).

Thirty-day survival / mortality has been a common focus of researchers and stakeholders. For example, the Centers for Medicare and Medicaid Services (CMS) reports on thirty-day mortality for a number of conditions on its Hospital Compare website. Compared to inpatient mortality, thirty-day mortality is believed to be less susceptible to manipulation by hospitals, who might, for example, seek to discharge patients who are likely to die.[1] Medicare Denominator files from CMS report date of death, validated against Social Security Administration records. We measure thirty-day survival by linking the Denominator files to Medicare Provider Analysis and Review Files on hospitalizations in the 50 U.S. states and the District of Columbia over the period 2003-2007.

We measure intensity of hospital care by the logarithm of the costs of a hospital stay. To do so, we apply cost-to-charge ratios from the Medicare Impact Files to total charges, including physician fees for services provided in the hospital. To make intensity comparable across areas, we adjust costs according to the Medicare Hospital Wage Index. We convert costs to 2011 dollars using the market basket for inpatient services from CMS. Following the literature on the returns to health care (Fisher, Wennberg et al. 2003), we aggregate adjusted costs to the area level by taking the average within Hospital Service Areas (HSAs) from the Dartmouth Atlas of Health Care (Doyle 2011). We restrict the analysis to urban areas, defined by an average population density of at least 1,000 persons per square mile residing within two miles of hospitals in an HSA in the 2000 Census. Intensity is measured at the condition level based on decedent cases, following (Fisher, Wennberg et al. 2003) and (Doyle 2011).

We estimate linear regressions of the following form:

$$S_{ih} = \beta_0 + \beta_I I_h + \beta_S S_i + \beta_A A_h + \mathbf{X_i \beta_X} + \mathbf{W_h \beta_W} + \boldsymbol{\theta}_{\mathbf{s(i)}} + \boldsymbol{\delta}_{\mathbf{t(i)}} + \varepsilon_{ih}, \quad \varepsilon_{ih} = \beta_s s_i + \beta_a a_h + \omega_{ih} \tag{2}$$

[1]The AHRQ IQIs focus on inpatient mortality, because inpatient mortality is typically available in administrative data on hospital discharges (Agency for Healthcare Quality and Research).

in which H_{ih} equals one if patient i treated at hospital h survived thirty days and zero otherwise, and I_h is the logged intensity of care (just described) in hospital *h's* area. In sensitivity analysis, we explore more flexible specifications of intensity.

We account for a variety of other factors in equation (2). A key strength of our analysis is the availability of a patient-specific measure of inpatient mortality risk S_i from the AHRQ IQIs. These measures are based on validated and published risk adjustment models, which incorporate not only age and sex, but also All Patient Refined Diagnosis Related Groups (APR-DRGs) and APR-DRG risk-of-mortality subclasses defined by patient diagnoses and medical procedures from the discharge records (Agency for Healthcare Quality and Research).

We also control for differences in adoption of low-cost but lifesaving technologies within a hospital's HSA, A_h. To do so, we follow (Skinner and Staiger)'s strategy of measuring processes of care that represent best practices, but do not contribute meaningfully to costs / intensity, for example, the provision of aspirin to heart-attack patients upon arrival at a hospital. We use the measures shown in Table 1. These measures are specific to care for heart attacks, congestive heart failure, and pneumonia, and endorsed by the Hospital Quality Alliance and publicly reported by CMS. Intensive care processes, such as percutaneous intervention (PCI) for heart attack, were excluded from our analysis.[2] For each condition, we perform a factor analysis of the relevant measures, and estimate an index of low-cost but effective technologies using a single-factor model (Skinner and Staiger). The 2007 reporting period was used to ensure the broadest availability of measures across hospitals; (Skinner and Staiger) find that differences in the adoption of technologies across hospitals are persistent over time.

To control for confounders of the intensity-mortality relationship, equation (2) includes patient age (5-year intervals beginning with age 65, plus 90 years old and older) and its square, gender, and race (white, black, Hispanic, and other.) Additional patient- and hospital-level

[2] Fibrinolytic medication within 30 minutes of arrival was not used because this measure was reported less frequently.

covariates motivated by a seminal study of health spending and mortality are also included (Fisher, Wennberg et al. 2003). These covariates include a patient's Charlson-Deyo co-morbidities (Deyo, Cherkin et al.), volume of patients at a hospital by patient type (Luft, Hunt et al.), and a hospital's teaching status (membership in Council of Teaching Hospitals) from the American Hospital Association Annual Surveys (American Hospital Association), and socio-demographic characteristics of the patient's zip code from the 2000 Census. Zipcode-level Census variables include median annual household income; average annual Social Security income; the percentage of the population who were living below the poverty level; were employed; had less than a high school education; were white, black, Hispanic or other; were single; were institutionalized elderly; and were non-institutionalized elderly with various disabilities. To deal with differences in cost of living across areas, household income in 1999 was deflated by the ACCRA Cost of Living Index by linking zip codes and cost indices at the level of the Combined Statistical Area. Income was categorized by approximate quartiles (<$30,000; $30,000 - $34,999; $35,000 - $44,999; $45,000+), with an additional category for missing values.

Table 2 presents summary statistics for the patients analyzed. The analysis also includes fixed effects for the states in which patients resided (Doyle 2011). Year fixed effects allow for secular trends in the determinants of mortality.

3.2 Initial analysis

The first specification of Table 3 reports estimation results for the full sample of patients admitted to the hospital on an emergency basis. Initially, we measure intensity by the log cost of a patient's hospital stay. A one log-point increase in intensity is associated with a 2.5 percentage point *decrease* in 30-day survival for patients with congestive heart failure, and a 5.2 percentage point decrease in survival for pneumonia patients (specification 1).

When patient mortality risk, the index of effective low-cost technology, and other covariates are included in the analysis (specification 2), the parameter estimates become positive, but are of negligible magnitude (0.007 and 0.005 for congestive heart failure and pneumonia). These findings are consistent with the body of evidence from Dartmouth researchers and others that more medical spending is not generally associated with better quality of care [e.g., (Fisher, Wennberg et al. 2003)].

In the case of heart attack, a one log-point increase in intensity is estimated to increase 30-day survival by 7.7 percentage points in a regression that includes only intensity. When patient mortality risk, hospital technologies, and other factors are incorporated, the magnitude of the effect becomes more positive (9.4 percentage points.)

In specification 3, intensity is measured by average costs among decedents at each hospital, then aggregated to the HSA level. Initially, the regressions include only intensity (specification 3). For each condition, the intensity parameter estimate is positive, and statistically and economically significant. The estimates for congestive heart failure and pneumonia increase to 0.023 and 0.030, respectively. Heart attack is again different, with its intensity parameter estimate decreasing from 0.094 to 0.040.

3.3 Dealing with unobserved patient heterogeneity: Ordinary least squares analysis of in-state versus out-of-state patients

We now distinguish between patients treated at hospitals in their state of residence, and out-of-state patients. As Table 2 shows, roughly 5% of patients were treated out-of-state, regardless of condition. Table 4 shows the results of the in-state and out-of-state comparison for regressions that include all covariates (specification 3 of Table 3.) For heart attack, the intensity parameter estimate is larger for out-of-state patients than for in-state patients, 0.053 versus 0.037, and this difference is statistically significant. For pneumonia, the out-of-state estimate is again larger (0.035 versus 0.029), but not significant. Altogether, these finding lend support to (Doyle)'s strategy of focusing on patients for whom the selection problem is arguably mild.

3.4 Dealing with residual production and patient heterogeneity: Instrumental variables

There may be residual heterogeneity with respect to patients and / or producers. We are particularly concerned about production heterogeneity, because a focus on patients whose health status is homogeneous does not deal with productivity differences across hospitals.

Appealing to the theories of hospital behavior discussed in Section 2, we use a variety of instruments for the intensity of hospital care. First, we measure insurer concentration using a Herfindahl-Hirschman index. Concentration has been publicly reported based on HMO and PPO enrollment as of January, 2005, using data from HealthLeaders and InterStudy. Concentration for 313 metropolitan standard areas in 44 states were linked to hospitals in our sample, and averages were taken by HSA. Second, we measure corporate tax rates by averaging the maximum marginal rate across years for each state, linking to hospitals within states, and averaging across hospitals within HSAs. The rates were obtained from the Tax Foundation. Third, we measure area wages using the Medicare Hospital Wage Index, averaging across years and hospitals within HSA.

Finally, we measure market size using the 2000 Census to quantify the population residing in zip codes within 2 miles of each hospital, and take the average across hospitals within each HSA. Hospital geo-coordinates are reported in AHA Annual Surveys (where unavailable, we use a hospital's zip code and its corresponding geo-coordinates from the 2000 Census). Individuals aged 65 or older are excluded from the population counts, because elderly individuals may be more likely to decide where to live based on their own health and area health-care resources.

Table 6 shows the results for the out-of-state patient samples. For all three conditions, the instruments have sizable first-stage F statistics, which range from 14.22 for heart attack to 31.05 for congestive heart failure. The results from first-stage regressions of intensity on the instruments (and all other covariates) are shown in Table 5. As predicted by theories of hospital behavior, intensity generally decreases with the insurer concentration index, corporate tax rates, and area wages, while increasing with market size. Because the instruments are logged, these results represent elasticities. Thus, the elasticity of care intensity for congestive heart failure with respect to the corporate tax rate is -0.122, while the elasticity of pneumonia intensity with respect to the insurer concentration index is -0.105.

The IV intensity parameter for heart attack is imprecisely estimated, and we cannot reject the hypothesis that intensity is exogenous. The parameter estimates are quite precise for congestive heart failure and pneumonia. Based on a Sargan-Hansen test, there is strong evidence for the endogeneity of the intensity of care intensity for congestive heart failure and pneumonia.

To interpret these findings, we report elasticities of 30-day mortality with respect to area-level intensity in Table 7. For out-of-state patients with heart attacks , we could not reject the exogeneity of intensity, and the elasticities based on the OLS results (Table 3) is -0.38. In the case of pneumonia, the elasticity increases in magnitude from -0.32 to -1.17 when we instrument for endogenous intensity.

We assess the validity of our instrumental variables analysis in a number of ways. First, note that our model is overidentified. As Table 6 shows, standard overidentification tests for model validity could not be rejected.

Next, we investigate how strong "selection on the unobservables" would have to be, for our IV results to represent "pure bias." (Altonji, Elder et al. 2005; Altonji, Elder et al. 2005; Altonji, Elder et al. 2008) develop a method for quantifying selection bias under the assumption that the relationship of an instrument to the observables in the equation of interest is as strong as its relationship to the equation's unobservable. To implement the method, we dichotomized log intensity as well as an instrument index constructed by fitting values from the first-stage regressions, , both based on median values. As Table 8 shows, survival was significantly higher in areas with above-median intensity, when we use the dichotomized instrument index. A survival regression that excludes intensity maintains an assumption of no intensity effect. Exogenous survival rates were constructed from fitted values of these regressions. Exogenous survival rates were compared based on values of the instrument index, just as the balance of individual covariates with respect to an instrument is assessed. Exogenous survival was higher in areas with above-median values of the instrument index, but only marginally so. For congestive heart failure, for example, 30-day survival in areas with the high instrument index was 90.36%, compared to 90.34% in areas with the low instrument index. As a consequence, the relationship between our instruments and unmeasured determinants of survival would have to be 1.99 times as strong as the relationship with measured factors, in order to negate our instrumental-variables results. Selection on unobservables would have to be even stronger to negate the findings for pneumonia patients.

Finally, we re-estimated the survival-intensity relationship using a limited set of instruments. Specifically, we continue to use insurance concentration and corporate tax rates. Market size was excluded, because large markets may be different in ways that are hard to distinguish from intensity; for example, outcomes tend to improve with volume, and larger markets may have greater volume. Wages are also excluded, because intensity is deflated by the wage index, and imperfect measurement of wages could lead to spurious correlation between the wage index instrument and intensity. Based on the limited instrument set, the results are quite similar, as Table 9 shows.

Finally, we address the possibility of heterogeneity in the returns to the intensity of hospital care by allowing the relevant parameter from equation (2) – specifically, β_I – to vary between areas with above-median and below-median intensity. The full instrument set still had reasonable power, with first-stage *F* statistics in excess of 10. However, there was no evidence of heterogeneity in returns.

Altogether, the results point to pervasive unobserved heterogeneity in the intensity-mortality relationship. For heart attack care, the intensity parameter estimate was substantially larger for patients treated at hospitals outside their state of residence than for in-state patients, and there was no evidence in our instrumental-variables analysis of endogenous intensity of care within the out-of-state patient sample. The results differed for congestive heart failure and pneumonia. There was considerable evidence of endogenous intensity, even (in the case of pneumonia) within the out-of-state patient sample for whom the selection problem should be mild. The selection problem may be less acute for heart attack, given its greater acuity. Even so, we could not distinguish between the in-state and out-of-state intensity parameters in the cases of congestive heart failure and pneumonia. The identification problem was apparent only in the instrumental-variables analysis.

A key motivation for this analysis was that productivity differences also represent a potentially significant threat to identification of the returns to hospital care. A model of hospital behavior suggests that more productive hospitals might supply greater intensity of care. Our finding from the IV analysis of downward bias in the returns to care is inconsistent with a *positive* productivity-intensity gradient.

4. Conclusions

This paper is concerned with the identification of production functions. In the context of health, there are two distinct threats to identification, unobserved patient heterogeneity and unobserved production heterogeneity.

To assess and deal with these threats to identification, we analyzed the intensity of area-level hospital care and thirty-day survival among Medicare beneficiaries admitted to a hospital on an emergency basis for heart attack, congestive heart failure and pneumonia.

We first distinguished between patients treated at hospitals in their state of residence, and out-of-state patients. The problem of patient selection should be mild for visitors (Doyle 2011). We found in ordinary least squares regressions that the marginal product of the intensity of medical care was positive, leading to increased survival for both in-state and out-of-state patients. The estimated effect size was significantly large for out-of-state patients with heart attacks.

Appealing to theories of hospital behavior, we used a variety of factors to instrument for the intensity of care, and found that the instruments were strongly related to intensity. When we instrumented for hospital intensity, we were able to reject the exogeneity of intensity for two of the three conditions studied (congestive heart failure and pneumonia), with the marginal product of intensity increasing substantially. Indeed, the elasticity of 30-day survival with respect to care intensity increased significantly in magnitude for pneumonia and congestive heart failure patients.

Our findings indicate that there is substantial unobserved heterogeneity in the production of health by hospitals. The downward bias that we found is consistent with a positive correlation between the intensity of hospital care and unobserved patient severity and / or a negative relationship between intensity and hospital productivity. Whether this evidence about the importance of unobserved patient and production heterogeneity for hospitals generalizes to other health production contexts is an open and important question.

Our finding that the returns to medical care are positive implies that it is likely that overall reductions in hospital spending will have adverse effects on patient outcomes. However, it is important to note some caveats for interpreting our findings. First, our findings do not imply that there are no avenues for reducing spending without hurting patient outcomes. In other words, it is possible that some spending is “wasteful” reducing such spending will not hurt patient outcomes. The returns to medical spending are context specific and are likely influenced by where and how spending is reduced. Second, our study is motivated by productivity differences across regions; however, it does not shed light on the root causes of such differences. Understanding whether such differences arise from failures of governance, poor public policies, or naturally occurring differences in specialization or skills can shed light on the extent to which these productivity differences can be eliminated. That is, how difficult or easy is it to increase productivity of low performing hospitals or regions, and how this can be done , are largely unknown. Finally, our study focused on variation in spending across regions, and it is certainly possible that there are large inefficiencies within hospitals or within regions. Identifying such inefficiencies and proposing policy solutions for correcting such inefficiencies is an important endeavor for future research.

References

Acemoglu, D. and J. Linn (2004). "Market Size in Innovation: Theory and Evidence from the Pharmaceutical Industry." Quarterly Journal of Economics **119**(3): 1049-1090.

Agency for Healthcare Quality and Research (2008). "Guide to Inpatient Quality Indicators."

Almond, D., J. J. Doyle, et al. (2010). "Estimating Marginal Returns to Medical Care: Evidence from At-risk Newborns." The Quarterly Journal of Economics **125**(2): 591-634.

Altonji, J. G., T. E. Elder, et al. (2005). "An Evaluation of Instrumental Variable Strategies for Estimating the Effects of Catholic Schooling." The Journal of Human Resources **40**(4): 791-821.

Altonji, Joseph G., Todd E. Elder, et al. (2005). "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools." Journal of Political Economy **113**(1): 151-184.

Altonji, J. G., T. E. Elder, et al. (2008). "Using Selection on Observed Variables to Assess Bias from Unobservables When Evaluating Swan-Ganz Catheterization." American Economic Review **98**(2): 345-350.

American Hospital Association (2006). 2005 Annual Survey. Chicago, IL, Health Forum, LLC.

Arellano, M. and S. Bond (1991). "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." The Review of Economic Studies **58**(2): 277-297.

Barnato, A. E., C. C. Chang, et al. (2010). "Is survival better at hospitals with higher "end-of-life" treatment intensity?" Med Care **48**(2): 125-132.

Card, D., C. Dobkin, et al. (2009). "Does Medicare Save Lives?" The Quarterly Journal of Economics **124**(2): 597-636.

Chandra, A. (2013). Economics Meets the Geography of Medicine.

Chandra, A. and D. O. Staiger (2007). "Productivity Spillovers in Health Care: Evidence from the Treatment of Heart Attacks." Journal of Political Economy **115**(1): 103-140.

Deyo, R. A., D. C. Cherkin, et al. (1992). "Adapting a clinical comorbidity index for use with ICD-9-CM administrative databases." Journal of Clinical Epidemiology **45**(6): 613-619.

Doyle, J. J. (2005). "Health Insurance, Treatment and Outcomes: Using Auto Accidents as Health Shocks." Review of Economics and Statistics **87**(2): 256-270.

Doyle, J. J. (2011). "Returns to Local-Area Health Care Spending: Evidence from Health Shocks to Patients Far from Home." American Economic Journal: Applied Economics **3**(3): 221-243.

Doyle, J. J., Jr., S. M. Ewer, et al. (2010). "Returns to physician human capital: evidence from patients randomized to physician teams." Journal of health economics. **29**(6): 866-882.

Finkelstein, A. (2003). Health Policy and Technological Change: Evidence from the Vaccine Industry. Cambridge, MA, National Bureau of Economic Research.

Fisher, E. S., D. E. Wennberg, et al. (2003). "The implications of regional variations in Medicare spending. Part 2: health outcomes and satisfaction with care." Annals of Internal Medicine **138**(4): 288-298.

Geweke, J., G. Gowrisankaran, et al. (2003). "Bayesian Inference for Hospital Quality in a Selection Model." Econometrica **71**(4): 1215-1238.

Gowrisankaran, G. and R. J. Town (1999). "Estimating the quality of care in hospitals using instrumental variables." Journal of Health Economics **18**(6): 747-767.

Griliches, Z. and J. Mairesse (1998). Production functions: the search for identification, Cambridge University Press.

Hodgkin, D. and T. G. McGuire (1994). "Payment levels and hospital response to prospective payment." Journal of Health Economics **13**(1): 1-29.

Kaestner, R. and J. H. Silber (2010). "Evidence on the Efficacy of Inpatient Spending on Medicare Patients." Milbank Q **88**(4): 560-594.

Luft, H. S., S. S. Hunt, et al. (1987). "The volume-outcome relationship: practice-makes-perfect or selective-referral patterns?" Health Services Research **22**(2): 157-182.

Marschak, J. and W. H. Andrews Jr (1944). "Random simultaneous equations and the theory of production." Econometrica, Journal of the Econometric Society: 143-205.

McClellan, M., B. J. McNeil, et al. (1994). "Does more intensive treatment of acute myocardial infarction in the elderly reduce mortality? Analysis using instrumental variables." JAMA **272**(11): 859-866.

Olley, G. S. and A. Pakes (1996). "The Dynamics of Productivity in the Telecommunications Equipment Industry." Econometrica **64**(6): 1263-1297.

Ong, M. K., C. M. Mangione, et al. (2009). "Looking Forward, Looking Back: Assessing Variations in Hospital Resource Use and Outcomes for Elderly Patients With Heart Failure." Circulation: Cardiovascular Quality and Outcomes.

Picone, G. A., F. A. Sloan, et al. (2003). "Does Higher Hospital Cost Imply Higher Quality of Care?" The Review of Economics and Statistics **85**(1): 51-62.

Robinson, J. C. and H. S. Luft (1985). "The impact of hospital market structure on patient volume, average length of stay, and the cost of care." Journal of Health Economics **4**(4): 333-356.

Romley, J. A., A. B. Jena, et al. (2011). "Hospital Spending and Inpatient Mortality: Evidence from California: An Observational Study." Annals of Internal Medicine **154**(3): 160-167.

Silber, J. H., R. Kaestner, et al. (2010). "Aggressive Treatment Style and Surgical Outcomes." Health Services Research **45**(6 Pt 2): 1872-1892.

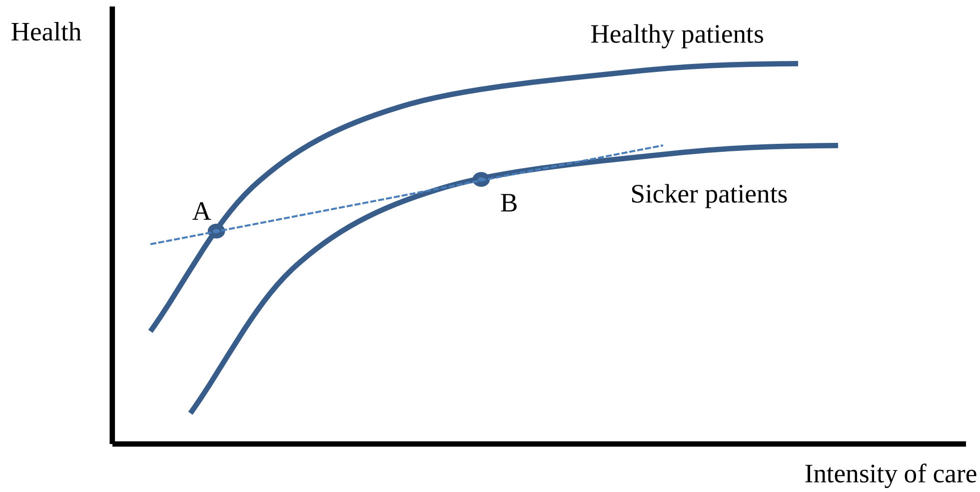
Skinner, J. (2011). Chapter Two - Causes and Consequences of Regional Variations in Health Care. Handbook of health economics. T. G. M. Mark V. Pauly and P. B. Pedro, Elsevier. **Volume 2:** 45-93.

Skinner, J. and D. Staiger (2009). Technology Diffusion and Productivity Growth in Health Care. Cambridge, MA, National Bureau of Economic Research.

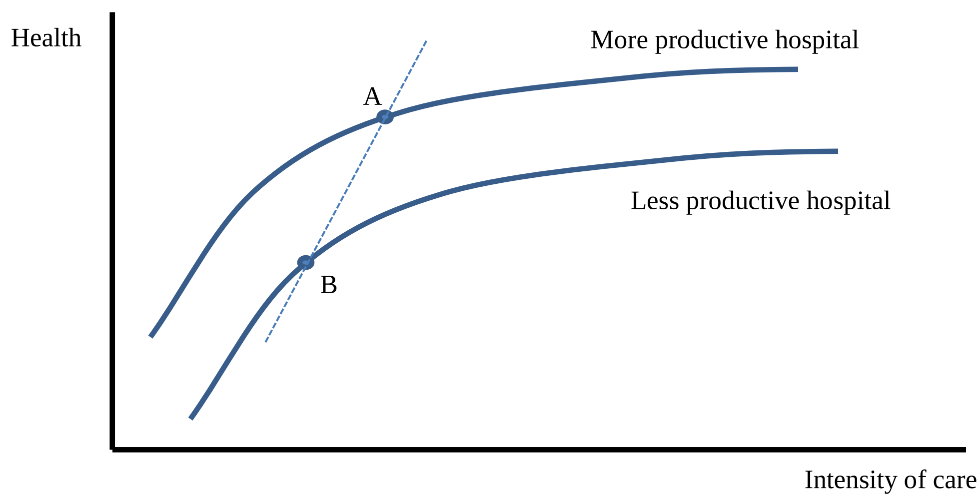
Skinner, J. S., D. O. Staiger, et al. (2006). "Is technological change in medicine always worth it? The case of acute myocardial infarction." Health Affairs **25**(2): w34-47.

Weinstein, M. and J. Skinner (2010). "Comparative Effectiveness and Health Care Spending--Implications for Reform." New England Journal of Medicine.

Figure 1: Threats to Identification of a Health Production Function



Marginal Product of Intensity of Hospital Care Understated,
If Patients with High Unobserved (to the Researcher) Severity Receive More Intensive Care



Marginal Product of Intensity of Hospital Care Overstated,
If Hospitals with High Unobserved (to the Researcher) Productivity Provide More Intensive Care

Table 1:
Process of Care Measures Underlying Productivity Estimates

Measure	Included in Productivity
Heart Attack	
Heart Attack Patients Given ACE Inhibitor or ARB for Left Ventricular Systolic Dysfunction	Yes
Heart Attack Patients Given Aspirin at Arrival	Yes
Heart Attack Patients Given Aspirin at Discharge	Yes
Heart Attack Patients Given Beta Blocker at Arrival	Yes
Heart Attack Patients Given Beta Blocker at Discharge	Yes
Heart Attack Patients Given Fibrinolytic Medication Within 30 Minutes Of Arrival	
Heart Attack Patients Given PCI Within 90 Minutes Of Arrival	
Heart Attack Patients Given Smoking Cessation Advice/Counseling	Yes
Congestive Heart Failure	
Heart Failure Patients Given Discharge Instructions	Yes
Heart Failure Patients Given Smoking Cessation Advice/Counseling	Yes
Heart Failure Patients Given an Evaluation of Left Ventricular Systolic (LVS) Function	Yes
Heart Failure Patients Given ACE Inhibitor or ARB for Left Ventricular Systolic Dysfunction	Yes
Pneumonia	
Pneumonia Patients Assessed and Given Influenza Vaccination	Yes
Pneumonia Patients Assessed and Given Pneumococcal Vaccination	Yes
Pneumonia Patients Given Initial Antibiotic(s) within 6 Hours After Arrival	Yes
Pneumonia Patients Given Oxygenation Assessment	Yes
Pneumonia Patients Given Smoking Cessation Advice/Counseling	Yes
Pneumonia Patients Given the Most Appropriate Initial Antibiotic(s)	Yes
Pneumonia Patients Whose Initial Emergency Room Blood Culture Was Performed Prior To The Administration Of The First Hospital Dose Of Antibiotics	

Table 2:
Summary Statistics for Patient Samples

Variable	AMI	CHF	Pneumonia
Patients, #	612,390	1,476,626	1,168,231
30-day survival, %	83.30 (37.30)	89.67 (30.43)	87.84 (32.69)
Cost per stay (2011 dollars)	18216 (5457)	15585 (5036)	15066 (4302)
Predicted inpatient survival, %	88.82 (10.14)	96.31 (4.09)	95.17 (5.18)
Age, years	79.3 (8.5)	80.3 (8.5)	80.4 (8.4)
Male, %	48.0 (50.0)	41.2 (49.2)	44.4 (49.7)
White, %	86.1 (34.6)	80.0 (40.0)	86.0 (34.7)
Black, %	9.1 (28.8)	15.0 (35.7)	8.9 (28.5)
Hispanic, %	1.9 (13.6)	2.3 (15.1)	2.1 (14.5)
Charlson-Deyo co-morbidities, #	2.4 (1.1)	2.3 (1.0)	1.6 (1.0)
Teaching hospital, %	25.5 (43.6)	21.1 (40.8)	18.0 (38.4)
Hospital volume, annual cases	198.4 (156.2)	370.3 (255.2)	257.8 (179.8)
In-state hospital, %	94.3 (23.2)	95.7 (20.2)	95.3 (21.1)
Year	2004.9 (1.4)	2005.0 (1.4)	2004.9 (1.4)
ZIP code demographics			
Median household income, $	40486(14801)	39188 (14862)	40444 (14995)
Below poverty line, %	11.2 (8.3)	12.2 (9.1)	11.4 (8.4)
Social Security income, mean, $	11526 (1482)	11373 (1525)	11480 (1487)
White, %	72.5 (26.0)	68.7 (28.4)	72.1 (26.1)
Black, %	12.1 (19.7)	15.2 (22.9)	11.8 (19.2)
Hispanic, %	10.0 (16.2)	10.8 (17.1)	10.5 (16.6)
Single, %	43.6 (9.3)	44.7 (9.8)	43.6 (9.3)
Less than high school, %	18.9 (10.9)	20.0 (11.5)	19.1 (11.2)
Employed, %	59.6 (9.2)	59.0 (9.2)	59.9 (8.9)
ZIP code health characteristics among population 65 and older			
Institutionalized, %	4.5 (5.1)	4.5 (5.1)	4.7 (5.2)
Physical disability, %	28.3 (6.8)	28.9 (6.8)	28.4 (6.8)
Mental disability, %	10.6 (4.2)	10.9 (4.3)	10.7 (4.2)
Sensory disability, %	13.8 (3.7)	13.8 (3.7)	13.8 (3.8)
Self-care disability, %	9.5 (3.7)	9.9 (3.8)	9.6 (3.7)
Home-bound disability, %	20.5 (5.7)	21.2 (5.9)	20.6 (5.7)

Notes: Standard deviations are in parentheses. AMI is acute myocardial infarction, or heart attack. CHF is congestive heart failure.

Table 3:
Regressions of 30-Day Survival on Area Hospital Intensity, by Patient Sample

Specification number	1	2	3
Controls for patient, hospital and area factors	N	Y	Y
Heart attack			
Log of patient costs / intensity	0.077*** (0.002)	0.094*** (0.001)	
Log intensity, average within area (HSA) among decedents			0.040*** (0.003)
Congestive heart failure			
Log of patient costs / intensity	-0.025*** (0.001)	0.007*** (0.001)	
Log intensity, average within area (HSA) among decedents			0.023*** (0.002)
Pneumonia			
Log of patient costs / intensity	-0.052*** (0.001)	0.005*** (0.001)	
Log intensity, average within area (HSA) among decedents			0.030*** (0.003)

Notes: Standard errors clustered at HSA level, and are reported in parentheses. * indicates statistical
5% level, and *** at the 1% level.

Table 4:
Regressions of 30-Day Survival on Area Hospital Intensity, In-State Patients Versus Out-of-State Patients

Patient sample	*In state*	*Out of state*
Heart attack	0.037*** (0.003)	0.053***^ (0.009)
Congestive heart failure	0.023*** (0.002)	0.020*** (0.006)
Pneumonia	0.029*** (0.003)	0.035*** (0.006)

Notes: Standard errors clustered at HSA level, and are reported in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. ^ indicates that out-of-state estimate differs from in-state estimate at the 10% level, ^^ at the 5% level, and ^^^ at the 1% level.

Table 5:
Elasticities of Area Hospital Intensity with Respect to Instruments from First-Stage Regressions for Out-of-State Patients

	Market size	*Corporate tax rate*	*Insurer concentration index*	*Wage index*
Heart attack	0.101*** (0.020)	-0.077** (0.038)	-0.053 (0.043)	-0.425*** (0.098)
Congestive heart failure	0.142*** (0.016)	-0.122*** (0.031)	-0.056 (0.042)	-0.165** (0.083)
Pneumonia	0.055*** (0.014)	-0.140*** (0.030)	-0.105*** (0.037)	-0.139* (0.084)

Notes: Standard errors clustered at HSA level, and are reported in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. Market size is number of persons under age 65 residing within 2 miles of hospital, averaged within Hospital Service Areas.

Table 6:
Instrumental-Variables Regressions
of 30-Day Survival on Area Hospital Intensity,
Out-of-State Patients

	First stage F statistic	*Hospital intensity parameter estimate*	*Endogeneity test, p value*	*Overidentification test, p value*
Heart attack	14.22	0.048 (0.030)	0.84	0.34
Congestive heart failure	31.05	0.056*** (0.013)	0.002	0.15
Pneumonia	13.15	0.126*** (0.026)	< 0.001	0.54

Notes: Standard errors clustered at HSA level, and are reported in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 7:
Elasticity of 30-Day Mortality with Respect to Area Hospital Intensity, Out-of-State Patients

Method	*OLS*	*IV*
Heart attack	-0.38	-0.35
Congestive heart failure	-0.20	-0.58^^^
Pneumonia	-0.32	-1.17^^^

Note: ^ indicates the IV estimate differs from OLS estimate at the 10% level, ^^ at the 5% level, and ^^^ at the 1% level.

Table 8:
Amount of Selection on Unobservables Relative to Selection on Observables Required To Attribute the Entire Effect of Above-Median Hospital Intensity to Selection Bias

Condition	$\hat{\beta}_I$	Exogenous survival rate, by IV index		*Selection ratio*
		Below median index	*Above median index*	
CHF	0.031*** (0.008)	90.34%	90.36%	1.99
Pneumonia	0.104*** (0.010)	89.235%	89.239%	40.5

Notes: CHF is congestive heart failure. $\hat{\beta}_I$ is instrumental variables estimate of above-median intensity on survival, based on above-median value of fitted instrument index from first-stage regression. Standard errors clustered at HSA level, and are reported in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. Exogenous survival rate is predicted survival from regression with intensity excluded.

Table 9:
Instrumental-Variables Regressions
with Instruments Limited to Corporate Tax Rate and Insurer Concentration Index,
Out-of-State Patients

	First stage F statistic	*Hospital intensity parameter estimate*	*Endogeneity test, p value*	*Overidentification test, p value*
Heart attack	14.22	0.048 (0.030)	0.84	0.34
Congestive heart failure	31.05	0.056*** (0.013)	0.002	0.15
Pneumonia	13.15	0.126*** (0.026)	< 0.001	0.54

Notes: Standard errors clustered at HSA level, and are reported in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.