GEOGRAPHIC KNOWLEDGE SPILLOVERS:
EVIDENCE FROM THE TREATMENT OF HEART ATTACKS

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Abstract

Knowledge spillovers are often cited as a reason for geographic specialization in production. We test the empirical implications of knowledge spillovers for specialization in the treatment of heart attacks. A large literature in economics and medicine documents persistent variation across areas in the use of surgical treatments for clinically identical patients, which is unrelated to average patient outcomes. We show that a very simple equilibrium Roy model of patient treatment choice with geographic knowledge spillovers can generate these facts. In addition, the model predicts that high-use areas will have *higher* returns to surgical management, better outcomes among patients most appropriate for surgery, and worse outcomes among patients least appropriate for surgery. We find strong empirical support for these and other predictions of the model, and decisively reject alternative explanations for the geographic variation in medical care.

When then an industry has once chosen a locality for itself, it is likely to stay there for good: so great are the advantages which people following the same skilled trade get from near neighborhood to one another. The mysteries of the trade become no mysteries; but are as it were in the air...[I]f one man starts a new idea it is taken up by others and combined with suggestions of their own; and thus becomes the course of yet more new ideas.

--Alfred Marshall, *Principles of Economics* (1890, p332).

I. Introduction

Since Marshall (1890), economists have used the concept of localized knowledge spillovers in production to rationalize the agglomeration of industries in certain parts of the country – software in Silicon Valley, furniture in North Carolina, and biotechnology in Cambridge, Massachusetts. Area specialization due to knowledge spillovers tends to be self reinforcing: the specialization of production increases the productivity of all local firms in that sector, while reducing the productivity of all other local firms (by reducing the local knowledge pool in the non-specialized sectors), further encouraging firms to specialize. Thus, small differences in local conditions can result in large differences in specialization and productivity, emphasizing the importance of path dependence and the potential "lock-in" of historical events (Arthur, 1989). While there is considerable evidence suggesting the existence of knowledge spillovers at the local level,[1] tests of the equilibrium implications of knowledge spillovers for specialization and productivity are less common.

We test the equilibrium implications of geographic knowledge spillovers in the context of the treatment of heart attacks (acute myocardial infarction or AMI). There are three reasons that the treatment of heart attacks is a particularly useful application for thinking about geographic knowledge spillovers. First, markets for heart attack treatment are geographically distinct. The acute nature of this condition requires immediate treatment and generally precludes a patient from traveling long distances to seek care. Therefore, unlike the production of computers or pharmaceuticals, it is possible to observe production in many distinct local markets. Second, the treatment of heart attacks is characterized by the choice between two competing interventions— intensive management characterized by the use of surgical or invasive interventions, and non-

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[1] For example, Zucker et al. (1988) link the timing of entry and location of biotechnology firms to the presence of academics that publish in basic science journals, while Jaffe et al. (1993) document that inventors tend to cite patents that were developed in the same geographic region. In medical care, there is a large literature on knowledge spillovers beginning with Coleman, Katz and Menzel (1957) who found that doctors who were more integrated with colleagues were the first to adopt a new drug. More recently, two randomized controlled trials by Soumerai et al. (1998) and Lomas et al. (1991) found that informational interventions targeted on "opinion leaders" improved quality of care among all community physicians. More broadly, Acemoglu and Angrist (2000) and Moretti (2003, 2004a,b) find evidence of human capital externalities on wages and productivity.

intensive management characterized by the use of drugs and other non-invasive interventions. Some geographic areas specialize in the intensive management of heart attacks, while others specialize in non-intensive management. Finally, unlike other markets, neither production choice can completely dominate a market because some patients are always more appropriate for a particular intervention (for example, 95 year old patients do not benefit from surgery, and must be treated non-invasively). Thus, the productivity of both intensive and non-intensive management can be observed in all markets.

We derive testable empirical implications of knowledge spillovers in an equilibrium model of regional specialization that uses insights from a prototypical Roy model as its building blocks. In our model regions specialize in the surgical or medical management of a condition. As the proportion of patients receiving a given treatment increases, knowledge spillovers increase the survival returns for all patients receiving this treatment, while simultaneously reducing the benefits from the alternative treatment. Thus, this model naturally generates higher returns to surgery in areas specializing in surgery, yet does not necessarily generate any relationship between specialization in surgery and overall mortality (because of the negative externality on patients receiving medical management). The knowledge spillovers have the ability to generate multiple-equilibria with different rates of surgery across areas, where a high-surgery equilibrium is not necessarily globally optimal (in the sense that an alternative equilibrium may produce the same overall survival returns).

Understanding variations in medical care is of interest in its own regard. Beginning with the work of Sir Allison Glover who documented significant variation in tonsillectomy rates across areas in the United Kingdom [Glover (1938)], an enormous body of literature in economics and medicine has documented variations in the use of intensive treatments across comparable locales. Traditional explanations such as sampling variation, differences in income and insurance, patient-preferences, and underlying health status do not explain these variations.[2] Surprisingly, area variation in the use of more intensive procedures is not associated with improved satisfaction, outcomes or survival (Fisher et al., 2003a,b and Baicker and Chandra (2004a,b).[3] This evidence raises important policy questions, given the large government role in payment for health care

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[2] Phelps (2000) provides an economists perspective of the immense literature on geographic variation in physician practice style. The medical literature on this topic is succinctly summarized in Chassin et. al (1987), Fisher et al (1994), Baicker and Chandra (2004a, 2004b) and the *Dartmouth Atlas of Health Care* [Wennberg and Cooper (1999) and Wennberg and Birkmeyer (2000)].

[3] Similar observations have been made by comparing treatments and outcomes in the US and Canada, where more aggressive management of AMI patients has no effect on mortality outcomes. For example, using a cohort of AMI patients, Tu et.al (1997) demonstrate that 30 percentage point difference in coronary angiography (and its attendant reperfusion procedures) between the US and Canada results in no differences in one year mortality.

through programs like Medicare: if higher rates of intensity do not translate into improved outcomes, is there a role for policy to move physicians or hospitals towards the "right rate"?

The answers to these questions are not easily forthcoming. The above facts stand in sharp contrast to the results of Randomized Clinical Trials (RCT) that consistently find gains from the surgical management of acute conditions that are routinely interpreted as evidence in support of more intensive management of patients.[4] These apparently conflicting findings can potentially be explained by diminishing returns. Whereas RCTs are performed on a group of patients most likely to benefit from the intervention, the lack of a cross-sectional relationship between intensity and outcomes is explained by a "flat of the curve" argument, where physicians perform the intervention until the marginal return is zero. Indeed, this is the interpretation that is used by McClellan et.al (1994) and McClellan and Newhouse (1997), to explain the small returns from more intensive treatments for heart attacks. Likewise, in the medical literature, Fisher et al. (2003b) argue that a 30 percent reduction in Medicare spending (such that spending in high use regions is reduced to that of low intensity areas) would not have any deleterious effects on patient outcomes or satisfaction.

While the diminishing returns model is intuitively appealing, it has a number of problems. First, there is no reason to expect wide variation in the use of treatments across areas that are similar, implying that the diminishing returns model is fundamentally a *disequilibrium* model and pareto improvements may be generated through the reallocation of resources. It is possible to explain area variations in this model by allowing for different marginal costs across areas or variants on supplier-induced demand, but such a model would generally predict a positive relationship between usage and outcomes (provided that not all areas were in the range of zero marginal benefits). A more fundamental problem with the diminishing returns model is that it predicts that the marginal benefit from more intensive patient treatment declines in areas that are more aggressive. But US-Canada comparisons using IV methods (Beck et al., 2003) and time-series comparisons (Pilote, McClellan, et al., 2003) suggest the opposite: the marginal benefit from more technologically intensive treatment in heart attack patients is larger in the US, where management of heart attacks is much more aggressive. As we discuss in the next section, these stylized facts are completely consistent with a model that incorporates geographic knowledge spillovers.

We organize our paper as follows. In Section II, we generalize a prototypical Roy model of specialization to allow for geographic knowledge spillovers, and derive a wide range of testable

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[4] See for example, Anderson et.al (2003) and Jacobs (2003). A review of over 23 trials by Keeley, Boura and Grines (2003) noted the demonstrated superiority of the intensive intervention over fibrionic therapy.

predictions of this model. In Section III we describe our data and estimation strategy. Section IV tests the implications of the model using chart-data from the CCP on a sample of Medicare beneficiaries who had a heart attack. Section V concludes and discusses the policy implications of our work including its implications for the interpretation of randomized clinical trials. In the data appendix to this paper we describe the precise details of our estimation sample.

II. A Model of Heart Attack Treatment with Knowledge Spillovers

We consider a simple model of patient treatment choice in the presence of knowledge spillovers. In this model, an individual patient chooses between two alternative treatments: intensive intervention (denoted s, since this treatment path usually involves surgery) versus non-intensive management (denoted m, since this option emphasizes medical management). The physician chooses the treatment option that maximizes expected utility, based on the expected survival rate ($Survival_s$, $Survival_m$) associated with each option. The survival rate from a given treatment option depends on patient characteristics (Z), but is also positively related to the fraction of all patients that receive the same treatment (P_s, $P_m=1-P_s$). Thus, a patient's choice of a specific treatment has a positive externality on all other patients receiving the same treatment.[5]

More formally, conditional on the fraction of patients receiving the treatment, let the survival rate associated with each treatment option take the simple form:

(1) $Survival_i = \beta_i Z + \alpha_i P_i, + \varepsilon_i$ for i=s,m.

The first term ($\beta_i Z$) represents an index of how appropriate a given patient is for each treatment based on medically relevant characteristics (Z). The second term ($\alpha_i P_i$) captures the knowledge spillover, which is positive if $\alpha > 0$. The final term (ε_i) represents factors that influence survival and which are known to the patient (or physician) at the time of choosing a treatment option but unobserved to the econometrician.

An individual patient receives the intensive treatment only if the survival benefit is positive. Therefore, the probability that an individual patient receives the intensive treatment is given by:

(2) $\Pr\{\text{intensive treatment}\} = \Pr\{ (Survival_s - Survival_m) > 0 \}$

$= \Pr\{ (\alpha_s + \alpha_m)P_s - \alpha_m + (\beta_s - \beta_m)Z > (\varepsilon_s - \varepsilon_m) \}.$

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[5] This feature is similar to how network externalities are modeled by Katz and Shapiro (1985, 1986). An alternative model, that we estimate and reject (see Table 8), uses: $Survival_i = \beta_i Z + \alpha_i N_i, + \varepsilon_i$ for i=s,m. Here, N is the number of patients in an area that receive the ith treatment. This alternative model predicts that larger areas are better are the use of both interventions.

Among the patients that choose the intensive treatment, the expected survival benefit is given by:

(3) $E[(\text{Survival}_s - \text{Survival}_m)|\text{intensive treatment}]$

$= (\beta_s-\beta_m)Z + (\alpha_s+\alpha_m)P_s - \alpha_m + E[(\varepsilon_s - \varepsilon_m)|\text{intensive treatment}].$

Thus, the expected survival benefit among patients receiving the intensive treatment (the treatment on the treated) depends on a patient's relative appropriateness for the treatment, the proportion of all patients that receive the intensive treatment, and a term representing the selection effect.

Equations (1)-(3) represent a standard Roy model except that, in equilibrium, P_s must be equal to the proportion of patients choosing the intensive treatment according to equation (2). Assuming that both Z and ε vary in the population, this implies the following equilibrium condition must hold:

(4) P_s $= E_Z [\Pr\{ (\alpha_s+\alpha_m)P_s - \alpha_m + (\beta_s-\beta_m)Z > (\varepsilon_s - \varepsilon_m) \}]$

$\equiv G(P_s).$

Thus, equilibrium in this model is defined as a solution to equation (4) (a fixed point). In other words, in equilibrium the proportion of patients choosing the intensive treatment must generate survival benefits to intensive treatment that are consistent with this proportion actually choosing the treatment.

This simple model has a number of very strong empirical implications. First, as illustrated in Figure 2, Equation (4) can generate variation across areas in the proportion of patients receiving the intensive treatment for two different reasons. For a given distribution of patients (which fixes the function G), there can be multiple equilibria because of the knowledge spillovers. For example, panel A illustrates a situation with two equilibria: An intensive equilibrium in which most patients receive surgical treatment and the returns to this treatment are high, and a non-intensive equilibrium in which few patients receive surgical treatment and the returns to this treatment are low (the middle point crossing point represents an unstable equilibrium). Alternatively, differences across areas in the distribution of patients (which changes the function G) will also lead to different equilibria.[6] For example, panel B illustrates a situation in which most of the patients in one area are more appropriate for surgery leading to an intensive equilibrium, while most of the patients in the non-intensive area are not appropriate for surgery. Even in the single equilibrium scenario the knowledge spillover increases the differences across areas: Having more surgically appropriate patients in an area (a shift upward in G) increases the return to surgical treatment for other patients, which in turn leads to a further increase in surgery

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[6] Arthur (1989) emphasizes the importance of "lock-in" by historical events. In our application, two regions might have differed in terms of their distribution of initial patient types. This difference is what caused the choice of present specialization.

(a move to the right along G). Thus, small differences in the distribution of patients can potentially generate large equilibrium differences in specialization across areas.

A second empirical implication of the model that follows immediately is that identical patients will be more likely to be treated intensively in an area where more patients are appropriate for intensive management of the heart-attack (based on Z). Any shift in the distribution of patients (Z) that results in a higher proportion being treated surgically (P_s) results in a higher probability of choosing surgery for each patient as a direct consequence of Equation (2). This implication is similar to that tested by Goolsbee and Klenow (2002) for individuals' purchase of home computers.

A number of additional implications of the model are illustrated in Figure 3. For simplicity, we ignore unobserved patient characteristics (ε) in this figure in order to focus on the intuition of the model. The top panel plots survival as a function of a patient's appropriateness for intensive management (which depends on Z) for each of the two treatment options (intensive and non-intensive). Patients to the left of the intersection of these two curves are treated non-intensively, while patients to the right are treated intensively. Patients further to the right are both more likely to receive intensive treatment, and experience higher returns to the treatment if treated. Thus, the model predicts that the return to surgery (treatment on the treated) is highest among patients with the highest probability of treatment.

The bottom panel of Figure 3 illustrates four additional implications of the model by comparing these survival curves between intensive and non-intensive areas. First, the quality of non-intensive management is worse in areas that are intensive. Thus, there should be a negative relationship between the proportion of patients that receive surgically intensive treatment and indicators of the quality of care for patients treated medically – i.e., intensive surgical treatment crowds out good medical management. A second implication of the model follows directly: In intensive areas survival will be higher among patients that are most appropriate for intensive management, but lower among patients that are more appropriate for medical management. In other words, the areas' specialization in intensive management helps patients that are appropriate for this type of care but hurts patients who require less intensive management. For example, to the extent that age is a crude proxy for requiring less intensive management, our model predicts that very-old patients are worse off being in an intensive area, while those who are younger benefit from their areas' specialization on the intensive margin. On net, however, overall mortality may be higher or lower in surgically intensive areas.

A third implication of our model is that the marginal patients receiving the intensive treatment in intensive areas will be less appropriate for the treatment than the average patient receiving the intensive treatment. As shown in the top panel of Figure 3, patients are given the

intensive surgical treatment if their appropriateness is above the point where the medical and surgical survival curves intersect. As seen in the bottom panel of Figure 3, this intersection is at a lower appropriateness level in intensive areas. Therefore, the additional patients receiving the intensive treatment in these surgically intensive areas are less appropriate than the patients receiving the intensive treatment in non-intensive areas.

A final implication of our model is that among those receiving intensive treatment, the survival benefit in the surgically intensive area is larger than the survival benefit in the medically intensive area. In other words, the treatment effect on the treated will be larger in more intensive areas. As can be seen in the bottom panel of Figure 3, this higher return is the net result of higher survival if patients are treated intensively and lower survival if patients are treated medically in the surgically intensive areas. Thus, the high return to intensive treatment in surgically intensive areas is the result of both a positive knowledge externality on intensive treatment and a negative knowledge externality on medical treatment.

Many of these implications would not be predicted in a model that does not allow for knowledge spillovers. For example, the flat-of-the-curve argument suggests a model in which there are no knowledge spillovers so that the survival return to intensive treatment for a given patient is the same everywhere. In this model, the higher treatment rates in some areas might be the result of excess capacity or financial incentives that lower the cost of providing intensive care and encourage the treatment of patients who receive little benefit. But such a model unequivocally predicts that the average survival benefit of intensive treatment will be lower for patients receiving the treatment in high-intensity areas. Moreover, since externalities play no role in the flat-of-the-curve argument, this model does not imply a lower quality of medical management or higher mortality among patients least appropriate for intensive treatment in high-intensity areas. Finally, the characteristics of other patients in the area play no role in determining treatment of a given patient in the flat-of-the-curve model, while this is a fundamental feature of models with knowledge spillovers.

In addition to having a wide range of testable empirical implications, the fundamental assumption of our knowledge spillovers model is quite plausible in health care. Much of physician learning about new techniques and procedures occurs from direct contact with other physicians ("see one, do one, teach one"), which leads to natural knowledge spillovers from practicing in an area in which physicians have specialized in a particular style of practice. A famous paper by Coleman, Katz and Menzel (1957) found that doctors who were the most integrated in a social-network (many colleagues named them as friends) were the first to adopt a new drug. Similarly, a randomized control trial that used "opinion leaders" in a hospital to try to improve care for AMI found large increases in beta-blocker and aspirin use and decreases in the use of outdated therapies

(Soumerai et al., 1998). Many studies have documented that patient outcomes are better in hospitals doing more surgery, and that hospital volume exerts an effect independent of the surgeon's own volume.

A second advantage of our model is that it is generally consistent with the key empirical regularities summarized in the introduction. In particular, our knowledge spillovers model can generate: (1) substantial differences across areas in the use of intensive procedures that is unrelated to average patient outcomes, (2) a negative correlation between surgical intensity and the quality of medical management of a condition, and (3) large returns to receiving the intensive intervention, particularly in high-intensity areas. Thus, a very simple equilibrium model of knowledge spillovers can rationalize all of the main stylized facts in the literature.

III. Data and Estimation.

Data

We focus our empirical work on the treatment of AMI for four reasons. First, cardiovascular disease, of which AMI is the primary manifestation, is the leading cause of death in the US. Each year about 1.5 million people in the United States have heart attacks; of these over 200,000 AMIs occur in the Medicare population alone. The toll in lives is heavy; about one-third of these patients die in the acute phase. Second, the acute nature of heart-attacks requires that the patient be immediately treated at the nearest hospital; a feature that reduces the possibility of selection where patients of a certain type seek care in another part of the country. Third, treatments for AMI are well understood and well measured—more intensive management relies on bypass and angioplasty as two procedures to restore blood-flow to the coronary arteries. We measure the use of this class of interventions by focusing on cardiac catheterization since it is a well-understood marker for surgically intensive management of patients (see for example, McClellan et.al (1994) and McClellan and Newhouse (1997)).[7] Alternatively, the non-intensive treatment regime would use fibrinolytics therapy (also known thrombolytics), that dissolve clots that may have formed in a blood vessel. These drugs are administered intravenously either as single injections or as a drip. Common thrombolytics include streptokinase and tissue Plasminogen Activator (tPA). Regardless of whether a patient is treated using intensively or using thrombolytics, patients should also be

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[7] In performing cardiac catheterization, a cardiologist inserts a thin plastic tube (catheter) into an artery or vein in the arm or leg, from where it is advanced into the chambers of the heart and into the coronary arteries. The catheter measures the bloods oxygen saturation and blood pressure within the heart. It us also used to get information about the pumping ability of the heart muscle. Catheters are also used to inject dye into the coronary arteries which can then be imaged to assess arterial stenosis using an x-ray. Catheters with a balloon on the tip (that is inflated in order to compress the atherosclerotic plaque to improve blood flow) are referred to as PTCA.

prescribed beta-blockers during their hospital stay that reduce the uptake of adrenalin and thereby slow the heart. Beta-blockers have been shown to improve outcomes for the majority of patients, their use is substantially below what most experts believe is appropriate, and the rate of beta-blocker use among AMI patients is a widely used measure of the quality of medical care [Jencks (2003), and Baicker and Chandra (2004a)]. Because beta-blockers are form of medical management of patients, their use serves as a marker of the quality of non-intensive medical management in an area. Finally, because mortality post-AMI is high, a well-defined endpoint is available to test the efficacy of alternative interventions.

Because acute myocardial infarction is both common and serious, it has been the topic of intense scientific and clinical interest. One effort to incorporate evidence-based practice guidelines into the care of heart attack patients, begun in 1992, is the Health Care Financing Administration's Health Care Quality Improvement Initiative Cooperative Cardiovascular Project. The CCP developed quality indicators that were based heavily on clinical practice guidelines developed by the American College of Cardiology and the American Heart Association. Information about more than 200,000 patients admitted to hospitals for treatment of heart attacks was obtained from clinical records. The CCP is considerably superior to administrative data (of the type used by McClellan et.al (1994)) as it collects chart data on the patients—detailed information is provided on laboratory tests, the location of the myocardial infraction, and the condition of the patient at the time of admission. In the data Appendix we provide a detailed account of the estimation sample used in this paper.

Defining Geography.

To construct local markets for health care we exploit insights from The *Dartmouth Atlas of Health Care.* The Atlas divides the U.S. into 306 Hospital Referral Regions (HRR), with each region determined at the zip code level by the use of an algorithm reflecting commuting patterns and the location of major referral hospitals. The regions may cross state and county borders, because they are determined solely by migration patterns of patients. For example, the Evansville, Indiana hospital referral region encompasses parts of three states because it draws patients so heavily from Illinois and Kentucky. HRRs are best viewed as the level where tertiary services such as cardiac surgery are received (although they are not necessarily the appropriate geographical level for primary care services). We describe the precise algorithm to construct the HRRs in the Data Appendix to the paper.

Analysis at the HRR level is preferable to analysis at the city, or state level since it uses the empirical pattern of patient commuting to determine the geographic boundaries of each referral

region, rather than assuming that the arbitrary political boundaries of states and cities also define the level at which the health care is delivered. Furthermore, for the purpose of studying geographic knowledge spillovers, an analysis at the HRR level is superior to one at the level of individual hospital for two reasons. First, patients can be assigned to HRR based on their residence, rather than based on the hospital at which they received treatment (which may be endogenous). In addition, geographic knowledge spillovers are likely to operate at a broader level than that of a given hospital. Physicians often have operating privileges in multiple hospitals and interact (socially and professionally) with other doctors who may or may not practice in their hospital, and patients are commonly referred to other hospitals within the HRR for treatment. Through such interactions, the entire area (as measured by HRRs) is more appropriate for analyzing equilibrium implications of knowledge spillovers.[8]

Estimation

The key estimating equations in this paper take the following form:

(5) $Outcome_{ijk} = \beta_{0k} + \beta_{1k} Intensive\ Treatment_i + X_i\Pi_k + u_{ijk}$

Here, $Outcome_{ijk}$ refers to either survival or costs for patient i in HRR j; k is an indicator variable that indexes the different groups for whom the effect of intensive management is sought (e.g., patients appropriate for intensive management versus not, or alternatively, high-intensity HHRs versus low intensity HRRs). Standard errors are clustered at the level of each area. The vector X_i includes the entire set of CCP controls listed in the data appendix. Our tables report estimates of β_{1k} and their difference between different sub-samples of the data; the latter is the central parameter of interest for the purpose of testing our model.

Following McClellan et.al (1994) and McClellan and Newhouse (1996), *Intensive Treatment* is measured by the receipt of cardiac catheterization within 30 days of the AMI. Alternatively, in some specifications we use total spending (Medicare Part A and Part B charges) in the first year after the AMI as a proxy for intensive treatment. The selection problem that confounds OLS estimation of the above equation is that CATH is recommended to patients who will benefit from the intervention and these patients are typically in better health, implying that

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[8] As an alternative to the use of HRRs we have also re-estimated our analysis using the U.S. Census Bureaus' "Metropolitan Statistical Area" (MSA) designation of urban areas. In general, HRRs may be thought of encompassing the relevant MSA with the addition of surrounding rural areas whose patients travel to the MSA to seek care. Using the MSA sample results in a loss of sample size, and introduces some noise into the IV analysis since within an MSA (such as Manhattan or Boston) there is much less variation in differential distance. The results reported in this paper are robust the use of MSAs, with the exception of the IV estimates which while not statistically different from what we report are very imprecise.

cov(Intensive Treatment, u) ≠ 0. Since the attending physician or cardiologist is likely to make the treatment choice based on information that is not observable in the CCP (for example, using information observed in the weeks following the initial admission), we follow the work of McClellan et.al (1994) and estimate equation (5) using instrumental variables. In particular, we use differential distance (measured as the distance between the patient's zip-code of residence and the nearest catheterization hospital minus the distance to the nearest non-cath hospital) as an instrument for intensive treatment. We capped differential distance at +/- 25 miles based on preliminary analysis that suggested little effect of differential distances beyond 25 miles on the probability that a patient receives catheterization.

To define a patient's clinical appropriateness for intensive management we estimate a logistic regression model for the probability of receiving cardiac catheterization within 30 days of the heart attack. Specifically we estimate:

(6) $Pr(Cardiac\ Cath_{ij})= G(\theta_0 + \theta_j + X_i\Phi)$

Here, θ_j is the risk-adjusted logistic index for the use of cardiac catheterization respectively in HRR j $(j=1,2,...,306)$. This equation is analogous to equation (2) in our model, with the HRR fixed effects capturing the externality that causes similar patients to be treated differently across areas. Fitted values from this regression, $Pr(Cardiac\ Cath_{ij})= \hat{G}(\theta_0 + X_i\Phi)$, are used as an empirical measure of clinical appropriateness for cardiac catheterization. For simplicity, in much of the empirical work we split the fitted values at their median to yield two equally sized groups; those above the median are appropriate for intensive management, and those below are not. In order to classify areas as being intensive versus not, we construct HRR level (risk-adjusted) catheterization rates by recovering the θ_j from the equation above.

IV. Empirical Results.

Table 1 presents IV estimates of the impact of CATH (as a marker for intensive treatment) on 1-year survival and 1-year costs (in thousands of 1996 dollars). In the first panel of Table 1 we present the analysis for all patients, and then the remaining panels estimate separate regressions by the clinical appropriateness of the patient. In the third column we instrument costs with differential-distance to estimate the cost-effectiveness of spending on survival. The results in Table 1 suggest that the returns to more intensive management of patients are increasing in clinical appropriateness, as predicted by our model. Patients appropriate for catheterization who received the intervention saw an 18.4 percentage point survival gain relative to appropriate patients who did not receive intensive therapy. For the less appropriate group, the effect of receiving catheterization is not statistically different from zero. Column 2 of the table demonstrates that it also costs more

to treat a patient who is clinically inappropriate for intensive management aggressively. One reason of this finding is the risk of iatrogenic (physician induced) complications that require additional rehabilitation days in the ICU or CCU. Column 3 uses total dollars spent on a patient as a measure of intensity. By this measure, increasing intensity (by spending an additional $1000 on a heart-attack patient) raises survival by 3.8 percentage points for patients who are appropriate for intensive management, but by nothing for patients who are not good candidates for intensive management. The lower panel of Table 1 provides an alternative breakdown of patients into appropriateness groups based on age (65-80 versus over 80). Clinical guidelines recommend that older patients not be treated surgically, suggesting that the returns to such treatment should be negligible for the over 80 group. The last panel of Table 1 confirms that this is indeed the case. Together, the results in Table 1 provide support for our Roy-model characterization of specialization—patients most appropriate for intensive treatment benefit most from such therapy, whereas those least appropriate for it do not benefit from it.

Table 2 explores the validity of differential distance as an instrument in our sample. Following McClellan et al. (1994), we split the sample in half and compare average characteristics of the sample above and below the median differential distance (-2.0 miles). The first two columns show that among all patients, there is a 6.1 percentage point difference in the CATH rate between the samples above and below the median, with higher differential distance to a CATH hospital associated with lower rates of CATH. A similar pattern is seen when the sample is restricted to patients who are most or least appropriate for CATH based on their propensity score or their age. Even among the patients with low propensity scores or over age 80, there is a 3-4 percentage-point decline associated with being further from a CATH hospital. These differences are all highly significant, even after controlling for the full set of patient controls from the CCP (the first-stage F-statistics on differential distance are over 50 for all specifications reported in Table 1).

The third and fourth columns of Table 2 report survival rates for patients above and below the median differential distance. If differential distance is unrelated to patient mortality risk, then these estimates can be combined with the difference in CATH rates from the first two columns to form a simple Wald estimate of the effect of CATH on survival. Among all patients, there is a 0.9 percentage point decline in survival associated with being further from a CATH hospital, suggesting that the intensive treatment associated with CATH leads to improved survival. The Wald estimate suggests that CATH is associated with a 15 percentage-point improvement in survival (.009 gain in survival / .061 increase in CATH), an estimate quite close to the 14.2 percent estimate from Table 1 that controlled for the full set of patient controls. The remaining rows show results for other patient samples that are similarly consistent with the Table 1

estimates, with a larger association between differential distance and survival seen among patients that are more appropriate for CATH and no relationship seen among patients that are less appropriate for CATH. Given the similarity of the Wald estimates to IV estimates with a full set of patient controls, it appears that differential distance is uncorrelated with observable differences in mortality risk. The fifth and sixth columns show that, as expected, there is little difference in the average 1-year predicted survival rate (from a logit of survival on the patient controls) for patients above and below the median differential distance.

The final two columns of Table 2 compare average 30-day predicted CATH rate (the propensity to get CATH) for only those patients getting CATH in the areas above and below median differential distance. If the additional patients getting CATH in the low differential distance sample were less appropriate for CATH, we would expect to see that the average patient getting CATH in these areas would have a lower propensity. In contrast, we see little difference in the sample that is nearer to a CATH hospital. Thus, it appears that differential distance is an instrument that increases CATH rates among a sample of patients that is very similar (at least on observable factors) to the average patient being treated. Therefore, it appears reasonable to interpret the IV coefficients as estimates of the treatment effect in the treated population.

In the remaining tables we evaluate the between-area predictions of our model. We begin with testing the simplest between-area implication: To be consistent with an economic model of specialization, our theoretical model predicts that as areas increase their intensity the additional patients receiving the intensive management should be less clinically appropriate for the intervention. In contrast, a non-economic model would predict that intensive areas simply perform more intensive treatments on all patients; there is no triage of patients into the treatment based on their appropriateness. To test this insight we estimate:

(7) $\qquad$ $Appropriateness_{ij} = \mu_0 + \mu_1\ ln(Cath\ Rate)_j\ + e_i$

The dependent variable is a measure of the appropriateness of a patient for cardiac cath (e.g., the propensity score), and the equation is estimated at the patient level *only for individuals receiving CATH*. The explanatory variable of interest is the natural logarithm of the risk-adjusted area CATH rate. Following the logic of Gruber, Levine and Staiger (1999), the coefficient μ_1 measures the difference in mean Appropriateness between the average and the marginal patient receiving the invasive treatment. If average appropriateness among patients getting CATH is declining as the CATH rate rises ($\mu_1 < 0$), we infer that the marginal patient getting CATH was less appropriate than the average patient (analogously to deriving marginal cost curves from average cost curves).

The results of estimating equation (7) are reported in Table 3. As the area's intensity increases, the marginal patient is 4.5 percentage points less likely to be appropriate for intensive treatments. As a robustness check, we included two alternative measures of clinical

appropriateness: age and a measure of clinical *ineligibility* for CATH as defined by the American College of Cardiologists (AHA) and the American Heart Association (AHA). Table 3 indicates that by both measures, the marginal patient is significantly less likely to be appropriate for cardiac catheterization.[9]

Figure 3 provides a graphical illustration of this relationship. For each of the 306 HRRs we graph the average propensity to receive cardiac catheterization (amongst patients who actually received it) against the log of the area risk-adjusted CATH rate. Using local-regression, we estimated the relationship between the average propensity and the risk-adjusted CATH rate and the slope of this line at each point (which we also smoothed). These estimates were then used to plot average and marginal patient receiving treatment. As seen in the figure, average appropriateness of patients getting CATH declines in more intensive areas. The average appropriateness can decline only if the marginal patient is less appropriate— as the lower line in Figure 3 indicates, the appropriateness of the marginal patient appears to be below the average patient and also declines as areas become more surgically intensive.

In addition to the above prediction, our model also predicts that the quality of medical management is worse in areas that are surgically intensive. Table 4 demonstrates that there is a negative relationship between indicators that an area is surgically intensive and indicators of the quality of care for patients treated medically – i.e., intensive surgical treatment crowds out good medical management. To measure the extent of intensive treatment in an area, we use the risk-adjusted 30-day CATH rate in each HRR. The risk-adjusted CATH rate reflects variation across areas in the probability that observationally identical patients will receive CATH, and therefore measures the knowledge externality through its role of increasing the probability of receiving the intensive treatment (see equation 2). Not surprisingly, this risk-adjusted CATH rate is positively correlated with other risk-adjusted rates of intensive surgical treatment such as bypass (CABG) and angioplasty (PTCA). More importantly, the negative correlation between the risk-adjusted CATH and beta-blocker rates supports the view that medical management is worse in surgically intensive areas. Risk-adjusted CATH rates are also negatively correlated with the number of non-invasive cardiologists per capita (cardiologists who did not perform CATH or surgery), suggesting that more surgically intensive areas have fewer physicians who focus on medical management.

The remaining rows of Table 4 report the correlation between risk-adjusted CATH rates and other area-level characteristics of interest. Risk-adjusted CATH rates are positively associated

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[9] Both measures are included as covariates in our estimation of the empirical appropriateness for cardiac catheterization. As such, these results are not three separate confirmations of the same prediction. The ACC/AHA measures are based on an evaluation of the patients chart characteristics and classify each patient as being ideal, appropriate, and inappropriate for catheterization; see Scanlon et.al (1999) for details.

with interventional cardiologists per capita (cardiologists who perform angioplasty), cardiovascular surgeons per capita (physicians who perform cardiac surgery), and the number of CATH labs per capita. These correlations are consistent with the view that a higher level of support services available in high-intensity areas may contribute to the externalities. The last three rows of this table demonstrate, perhaps surprisingly, that risk-adjusted CATH rates are not strongly associated with demographic characteristics of the HRR such as population, income, or education.

A more fundamental implication of knowledge externalities is that the same patient will be more likely to receive intensive treatment in an area where more patients are appropriate for this type of treatment – i.e. the characteristics of other patients in the population will influence the treatment choice of an individual. Empirically, this implies that risk-adjusted CATH rates should be higher in areas where the average patient is more appropriate for CATH. In the first column of Table 5 we regress risk-adjusted CATH rates on the average propensity to get CATH in each HRR. The coefficient is statistically significant and implies that for every 1 percentage point increase in the expected CATH rate (based on patient characteristics), there is an additional 0.71 percentage point increase in the area CATH rate because of spillovers. In the second column we control for area demographics which could potentially confound this relationship, but they are insignificant and do not materially change the coefficient. In the final two columns, we repeat this exercise using the risk-adjusted beta-blocker rate as the dependent variable. The model implies that we should see the opposite effect in these regressions, as the rise in CATH-appropriate patients exerts a negative externality on the quality of medical care. The coefficient on the average propensity to get CATH is negative and significant, implying that every 1 percentage-point increase in the expected CATH rate reduces the use of beta blockers by 0.75 percentage points. This estimate is also robust to controls for area demographics, although the percentage of the population under age 65 and per capita income both have significant effects on beta-blocker use.

In Table 6 we examine another prediction of the knowledge-externalities model that cannot be reconciled by other models. In order to test whether the return to intensive management is higher in high-intensity areas versus low intensity ones, we use our estimates of HRR level intensity from the estimation of equation (6) to classify patients as being treated in high or low intensity regions (as measured by whether the risk-adjusted CATH rates is above or below the median rate). In Table 6, we report IV estimates of the effect of receiving intensive management within each of these two groups. The results of this analysis are reported in a manner that mirrors the estimates in Table 1. The survival returns to intensive management in intensive areas is roughly three times the return observed in low intensity areas, while there is no statistically

significant difference in the costs associated with the different areas. As an alternative test, we should also find that those areas with poor medical management have better outcomes from the use of intensive procedures. In the next panel of Table 6, we classify patients into areas of differing intensity based on the area's risk-adjusted beta-blocker usage rates. High beta-blocker usage is an indicator of high quality medical management, suggesting that these areas have specialized in medical management and therefore should have a low return to intensive treatment. Once again, we note the dramatic degree to which the predictions of area specialization are at work: The impact of CATH on survival is much smaller in areas with good medical management.

Finally, Table 7 tests a unique implication of knowledge externalities: Patients most appropriate for intensive treatments are better off being treated in high-intensity areas, while patients who are least appropriate for intensive treatments should be worse off in such areas. To test this prediction we split patients into 3 equal-sized groups of appropriateness for intensive treatments. Within each group, we report the relationship between survival and the area CATH rate in the first column. We also report the relationship between spending and the area rate in the second column. The first panel of Table 7 replicates the central finding from the area-variations literature—area intensity is associated with costs but not associated with improved outcomes among patients as a whole. However, as the second panel demonstrates this finding masks significant heterogeneity in the effect of intensive by patient appropriateness. Patients appropriate for intensive managements clearly benefit from being treated in intensive areas. However, as the knowledge externality predicts, patients least appropriate for intensive treatments are harmed as a result of being treated in intensive areas. The size of the negative externality is surprisingly large—increasing area CATH intensity by ten percentage points (0.1) would reduce the survival of patients least appropriate for CATH by 0.75 percentage points. This finding holds true (although less significant) when we split the data by alternative indicators of appropriateness for intensive treatment, including age and ACC/AHA guidelines.

Our model suggests that patients who are inappropriate for CATH are worse off in intensive areas because (1) the quality of medical management in these areas is worse than in other areas, and (2) few of these patients receive intensive treatment, even in the more intensive areas. The last two columns of Table 7 explore these two dimensions of care directly by estimating the relationship between area CATH intensity and the rate at which patients receive beta blockers (as an indirect marker of quality of medical management) and CATH (as a direct marker of intensive management).   Beta-blocker use is lower among all patient groups in the high intensity areas, suggesting that quality of medical management is generally poor in these areas. At the same time, CATH rates among those patients least appropriate for CATH rise much less in high intensity areas than for other patients. Thus, worse outcomes for this group appear to result from worse

medical management in areas with high CATH intensity, as our model predicts.

Medical practice guidelines recommend that nearly all patients receive beta blockers, independent of whether they are treated intensively or non-intensively. Nevertheless, one might be concerned that lower beta-blocker use in high CATH intensity areas was simply the mechanical substitution of surgery for beta blockers among a subset of patients, rather than a broad indicator of low quality medical management. Figure 4 provides two pieces of evidence against this mechanical interpretation. This figure plots the percent of patients who receive beta-blockers during hospitalization against patient appropriateness for catheterization (estimated by a running regression) in HRRs with risk-adjusted CATH rates above and below the median. First, the use of beta blockers is actually higher among patients that are more appropriate for CATH, which is the opposite of the mechanical substitution explanation. Furthermore, we see that intensive areas are less likely to provide beta-blockers to *all* patients (as was seen in Table 7), suggesting that these areas provide poor quality medical management to all patients.

Finally, our analysis has assumed that knowledge spillovers depend on the proportion of patients receiving a given treatment, rather than the absolute number. Alternatively, knowledge spillovers could be more prevalent in larger areas; larger HRRs such as Los Angeles or Manhattan may excel at both the intensive and non-intensive delivery of care. To explore this hypothesis further, we estimate the relationship between alternative measures of HRR size and patient survival in Table 8. We regress 1-year survival on patient risk-adjusters, the risk-adjusted CATH rate and the log of the resident population (first 4 columns) and log of AMIs per hospital (last four columns). Table 8 demonstrates that the size measures are largely insignificant—larger areas do not result in improved survival. On the other hand, the "externality" (as measured by the HRR CATH rate) is always protective of patients who are appropriate for CATH and harmful for inappropriate patients.

V. Conclusion

A very simple equilibrium model of patient treatment choice with geographic knowledge spillovers appears to rationalize the main stylized facts concerning variation across areas in the use of technologically intensive medical care. The model yields a range of additional empirical implications, which we found uniform support for in our analysis of treatment for heart attacks. Alternative models, such as those based on "flat-of-the-curve" medicine and supplier-induced demand, have fundamentally different implications that are clearly rejected by the data. Thus, there appears to be strong empirical support for a Marshallian-style model of specialization with knowledge spillovers.

Although knowledge spillovers are the most natural interpretation of our model and

empirical results, there are certainly other mechanisms that could generate similar spillovers. For example, the spillovers may come from a form of network externality, in which specialization in a given treatment results in better support services arising in the area (e.g. specialized surgical centers, nursing staff, etc.). Alternatively, area specialization may attract physicians with a comparative advantage in that specialty, thereby generating better outcomes within the narrow specialty but worse outcomes more broadly. These models share the key feature that specialization in one sector improves productivity in that sector while reducing productivity elsewhere, thereby reinforcing the tendency to specialize.

The implications of our findings go well beyond the treatment of heart attacks. To the extent that knowledge spillovers are a common feature of many sectors, our results provide compelling evidence that such spillovers are an important feature of geographic specialization. Moreover, our results provide some of the first direct evidence of the negative externalities imposed on a subset of the population because of equilibrium pressures towards specialization. Such negative externalities are a central component of arguments for government intervention. Finally, our model has interesting empirical implications when applied to the more general question of human capital externalities. For example, our model would suggest that people living in areas with higher ability populations would be more likely (holding ability constant) to go to college, the return to going to college in these areas would be higher, but wages of low ability people in these areas would be lower. In principal, these are all testable implications.

Our results also raise important questions about what can be learned from randomized controlled trials in medicine. While randomized trials are considered the gold standard for determining the effectiveness of a given medical treatment, they are designed to provide a partial-equilibrium estimate of the treatment effect in a well-defined population. But with knowledge spillovers, the general equilibrium effect of adopting a new treatment could be smaller or larger than the partial equilibrium estimate of treatment effectiveness, because of the negative externality imposed on patients who are more appropriate for an alternative treatment and the positive externality on patients who are more appropriate for the new treatment. This general-equilibrium effect is not identified in a typical randomized trial, but could potentially be estimated in a trial that randomized across areas rather than individuals. In addition, the effectiveness of the treatment depends on where the trial is conducted (just as our IV estimates depended on intensity in the area): Surgical interventions may perform poorly in an area that specializes in medical management of its patients and perform well in a more surgically intensive area. As such the external validity of a randomized trial is compromised.[10]

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[10] For example, Anderson et.al (2003) RCT results that angioplasty resulted in better outcomes (as measured

The presence of knowledge spillovers may justify a policy intervention to ameliorate the deleterious effects of the externality. However, evaluating the welfare implications of any proposed intervention is not a trivial exercise. Understanding what policy lever to push hinges importantly on whether the variations observed in the data are the consequence of single or multiple equilibria. With multiple equilibria we may be able to identify areas stuck in sub-optimal equilibrium, and one-time interventions that "shock" the system to a different equilibrium would be called for (for example the experiment in O'Connor et al. (1996)). With single equilibrium, knowledge spillovers can generate either too much or too little intensive treatments, depending on the size of the externalities and the distribution of patients in the area, and interventions must be sustained in order to alter the equilibrium outcome. Thus, from a policy perspective, the evidence to date has little to say about whether there is any reason to reduce the variation across areas in the use of technologically intensive treatments or, if so, what would be the appropriate policy response.

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by reinfarction, 30 day mortality, or stroke) over fibrinolytic therapy despite the fact that it takes additional time to get the patient to an angioplasty capable hospital. The accompanying editorial by Jacobs (2003) concludes that patients should be referred angioplasty capable hospitals.

Data Appendix

I. Construction of Hospital Referral Regions. Hospital Referral Regions are constructed using a two part algorithm.

Step 1: All acute care hospitals in the 50 states and the District of Columbia were identified from the American Hospital Association Annual Survey of Hospitals and the Medicare Provider of Services files and assigned to a location within a town or city. The list of towns or cities with at least one acute care hospital (N=3,953) defined the maximum number of possible Hospital Service Areas (HAS). Second, all 1992 and 1993 acute care hospitalizations of the Medicare population were analyzed according to ZIP Code to determine the proportion of residents' hospital stays that occurred in each of the 3,953 candidate HSAs. ZIP Codes were initially assigned to the HSA where the greatest proportion (plurality) of residents were hospitalized. Approximately 500 of the candidate HSAs did not qualify as independent HSAs because the plurality of patients resident in those HSAs were hospitalized in other HSAs. The third step required visual examination of the ZIP Codes used to define each HSA. Maps of ZIP Code boundaries were made using files obtained from Geographic Data Technologies (GDT) and each HSA's component ZIP Codes were examined. In order to achieve contiguity of the component ZIP Codes for each HSA, "island" ZIP Codes were reassigned to the enclosing HSA, and/or HSAs were grouped into larger HSAs. This process resulted in the identification of 3,436 HSAs, ranging in total 1996 population from 604 (Turtle Lake, North Dakota) to 3,067,356 (Houston) in the 1999 edition of the Atlas. Intuitively, one may think of HSAs as representing the geographic level at which "front end" services such as diagnoses are received.

Step II: Hospital service areas make clear the patterns of use of local hospitals. A significant proportion of care, however, is provided by referral hospitals that serve a larger region. Hospital referral regions were defined in the *Dartmouth Atlas* by documenting where patients were referred for major cardiovascular surgical procedures and for neurosurgery. Each hospital service area was examined to determine where most of its residents went for these services. The result was the aggregation of the 3,436 hospital service areas into 306 hospital referral regions that were named for the hospital service area most often used by residents of the region. Thus if a Medicare enrollee living in Hartford, CT were admitted to a hospital in Boston, MA, the utilization would be attributed to Hartford, and not to Boston. This assignment avoids the serious shortcoming of unusually high utilization rates in large referral centers such as Boston or Rochester, MN.

II. Construction of CCP Estimation Sample:

The CCP used bills submitted by acute care hospitals (UB-92 claims form data) and contained in the Medicare National Claims History File to identify all Medicare discharges with an International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) principal diagnosis of 410 (myocardial infarction), excluding those with a fifth digit of 2, which designates a subsequent episode of care. The study randomly sampled all Medicare beneficiaries with acute myocardial infarction in 50 states between February 1994 and July 1995, and in the remaining 5 states between August and November, 1995 (Alabama, Connecticut, Iowa, and Wisconsin) or April and November 1995 (Minnesota); for details see O'Connor et.al (1999). The Claims History File does not reliably include bills for all of the approximately 12% of Medicare beneficiaries insured through managed care risk contracts, but the sample was representative of the Medicare fee-for-service (FFS) patient population in the United States in the mid-1990s. After sampling, the CCP collected hospital charts for each patient and sent these to a study center where trained chart abstracters abstracted clinical data. Abstracted information included elements of the

medical history, physical examination, and data from laboratory and diagnostic testing, in addition to documentation of administered treatments. The CCP monitored the reliability of the data by monthly random reabstractions. Details of data collection and quality control have been reported previously in Marciniak et.al (1998). Finally, the CCP supplemented the abstracted clinical data with diagnosis and procedure codes extracted from Medicare billing records and dates of death from the Medicare Enrollment Database.

For our analyses, we delete patients who were transferred from another hospital, nursing home or emergency room since these patients may already have received care that would be unmeasured in the CCP. We transformed continuous physiologic variables into categorical variables (e.g., systolic BP < 100 mm Hg or ≥ 100 mm Hg, creatinine <1.5, 1.5-2.0 or >2.0 mg/dL) and included dummy variables for missing data. We used date of death to identify patients who did or did not survive through each of three time points: 1-day, 30-days, and 1-year after the AMI. For all patients, we identified whether they received each of 6 treatments during the acute hospitalization: reperfusion (defined as either thrombolysis or PCI within 12 hours of arrival at the hospital), aspirin during hospitalization, aspirin at discharge, beta-blockers at discharge, ACE inhibitors at discharge, smoking cessation counseling, and each of 3 treatments within 30-days of the AMI: cardiac catheterization, PCI, or CABG. We used the ACC/AHA guidelines for coronary angiography to identify patients who were ideal (Class I), uncertain (Class II), or inappropriate (Class III) for angiography; these details are provided in Scanlon et.al (1999).

For each AMI patient we computed Medicare Part A and Part B costs within 1 year by weighting all Diagnosis Related Groups (DRGs) and Relative Value Units (RVUs) nationally. This measure of costs abstracts from the geographic price adjustment in the Medicare program.

III. Construction of clinical appropriateness index, HRR cathetherization rates, and HRR beta-blocker rates.

To compute this index we estimate a logistic regression model for the probability of receiving cardiac catheterization within 30 days of the heart-attack. We estimate:

$Pr(Cardiac\ Cath_{ij})= F(\theta_0 + \theta_j + X_i\Phi)$

$Pr(Beta\ Blockers_{ij})= F(\theta_0 + \Pi_j + X_i\Phi)$

Fitted values from this regression, Pr(Cath|X), are used as an empirical measure clinical appropriateness for cardiac catherterization. The HRR fixed effects for the use of cardiac catheterization and beta-blockers are obtained as θ_j and Π_j respectively. Included in this model are the following risk-adjusters:

1. Age, Race, Sex (full interactions)
2. previous revascularization (1=y)
3. hx old mi (1=y)
4. hx chf (1=y)
5. history of dementia
6. hx diabetes (1=y)
7. hx hypertension (1=y)
8. hx leukemia (1=y)
9. hx ef <= 40 (1=y)
10. hx metastatic ca (1=y)
11. hx non-metastatic ca (1=y)
12. hx pvd (1=y)
13. hx copd (1=y)
14. hx angina (ref=no)
15. hx angina missing (ref=no)
16. hx terminal illness (1=y)
17. current smoker
18. atrial fibrillation on admission
19. cpr on presentation
20. indicator mi = anterior
21. indicator mi = inferior
22. indicator mi = other
23. heart block on admission
24. chf on presentation
25. hypotensive on admission
26. hypotensive missing
27. shock on presentation
28. peak ck missing
29. peak ck gt 1000
30. non-ambulatory (ref=independent)
31. ambulatory with assistance
32. ambulatory status missing
32. albumin low(ref>=3.0)
33. albumin missing(ref>=3.0)
34. bilirubin high(ref<1.2)
35. bilirubin missing(ref<1.2)
36. creat 1.5-<2.0(ref=<1.5)
37. creat >=2.0(ref=<1.5)
38. creat missing(ref=<1.5)
39. hematocrit low(ref=>30)
40. hematocrit missing(ref=>30)
41. ideal for CATH (ACC/AHA criteria)

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Figure 1: Multiple (Panel A) versus Single Equilibrium (Panel B) Characterizations of Area Variations.

G(P_S)

Intensive Area

Non- Intensive Area

0.0 P_s= Proportion of patients getting intensive treatment   1.0

G(P_S)

Intensive Area

Non- Intensive Area

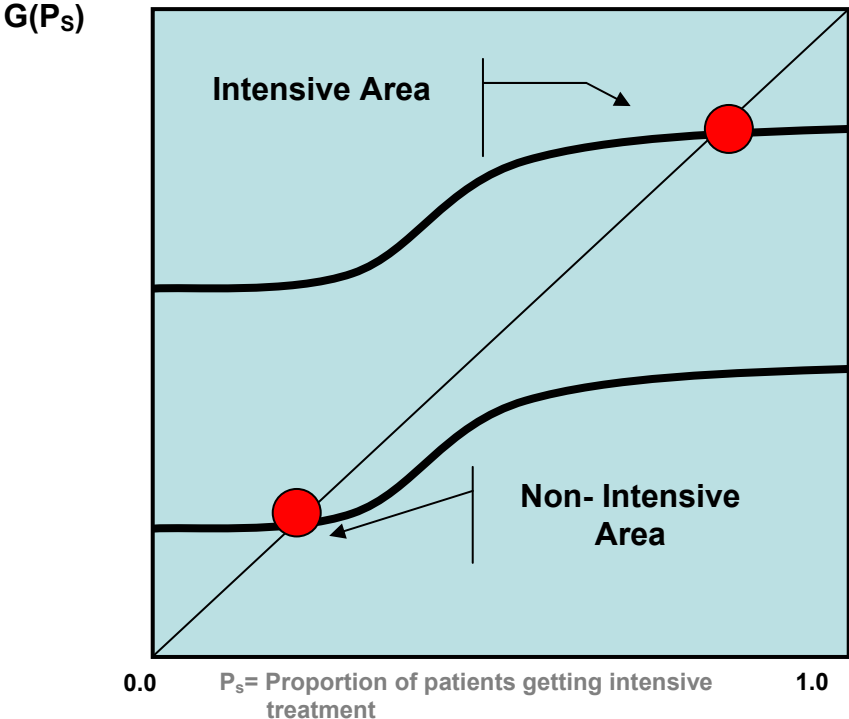0.0 P_s= Proportion of patients getting intensive treatment   1.0
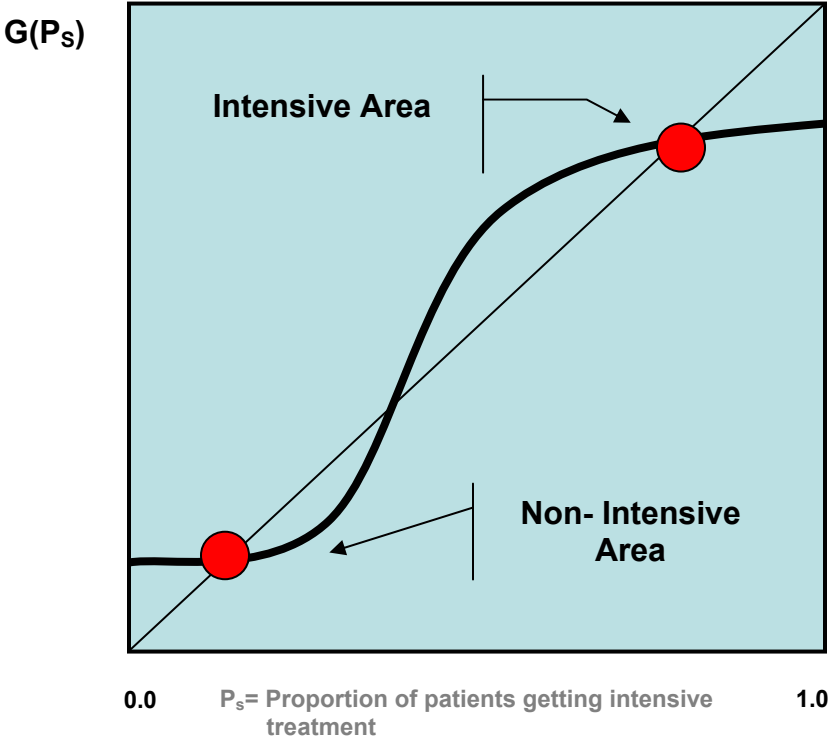
Figure 2: Graphical Illustration of Specialization with Knowledge Spillovers
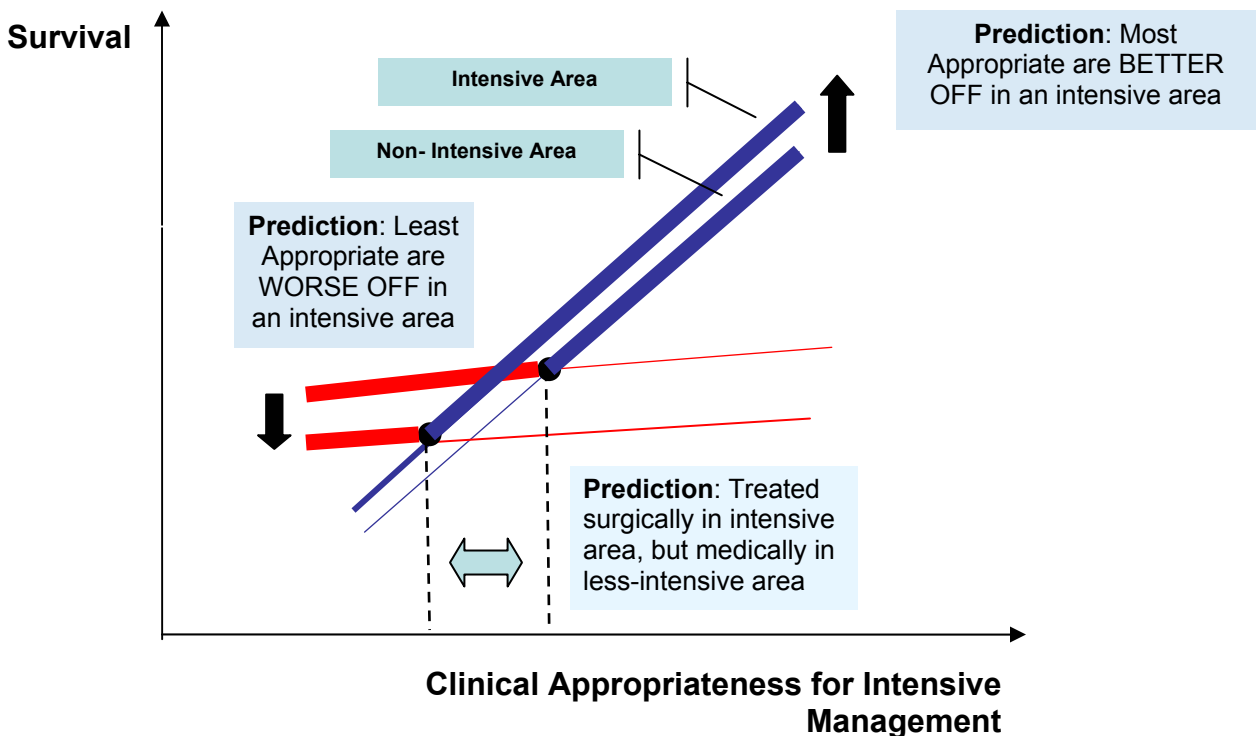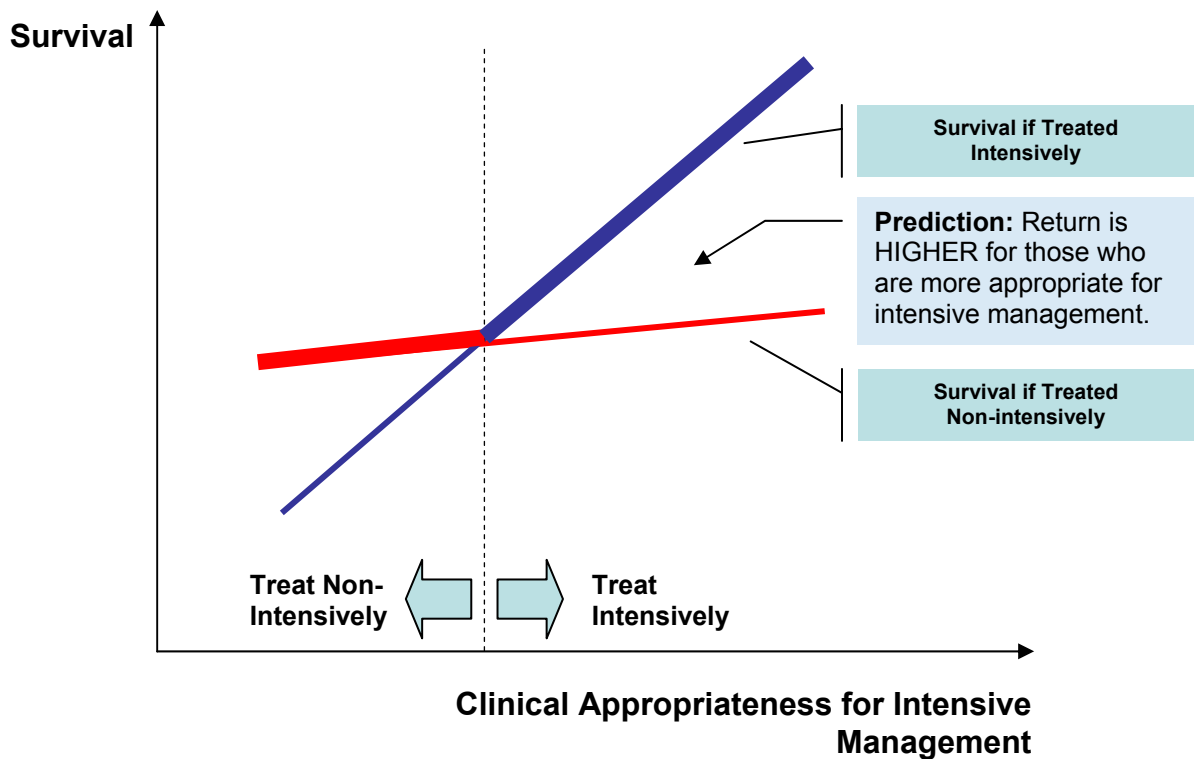
Panel A describes the relationship between two alternative ways to treat patients within an area. The survival production possibilities frontier describes the best treatment for a patient of given clinical appropriateness. The model predicts that the returns to intensive management are increasing in patients' appropriateness for such interventions. Panel B contrasts the care across two areas that differ in their surgical intensity. The knowledge spillover results in patients appropriate for intensive management being better off in the surgically intensive areas, whereas patients appropriate for non-intensive management being worse off in such areas. See Section II of text for details and formal model.

Figure 3: Relation Between Average Patient and Marginal Patient Receiving Cardiac Catheterization

Figure 4: Percent of Patients Getting Beta Blockers by Patient Propensity to Get Cath In HRRs With Low (Top Line) and High (Bottom Line) Risk-Adjusted Cath Rate.
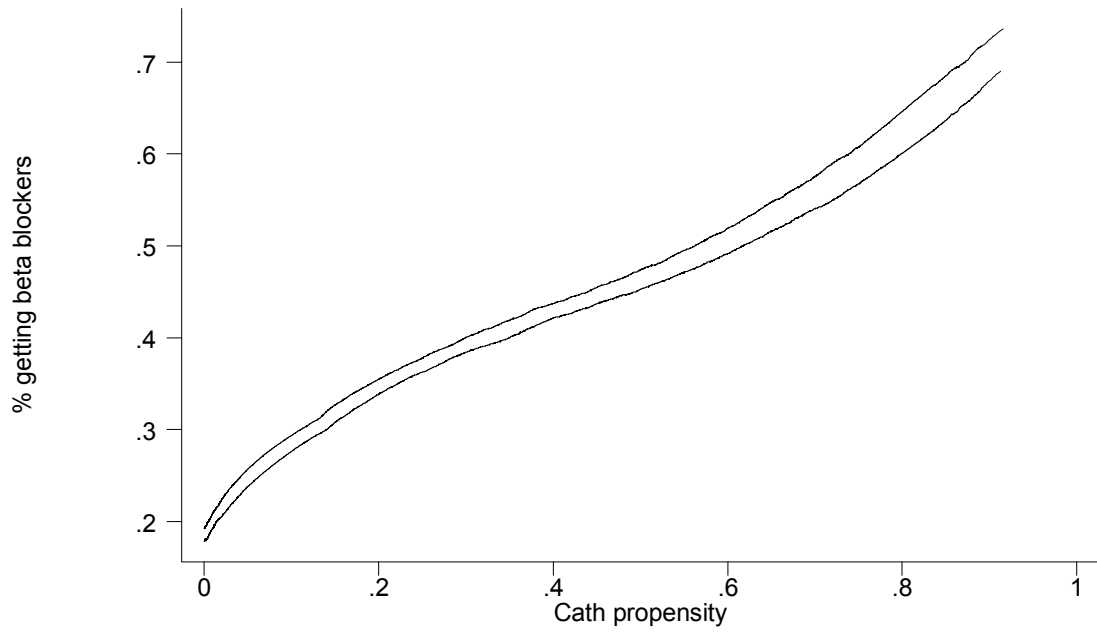
Table 1: Instrumental Variable Estimates of Intensive Management and Spending on 1 Year Survival by Clinical Appropriateness of Patient

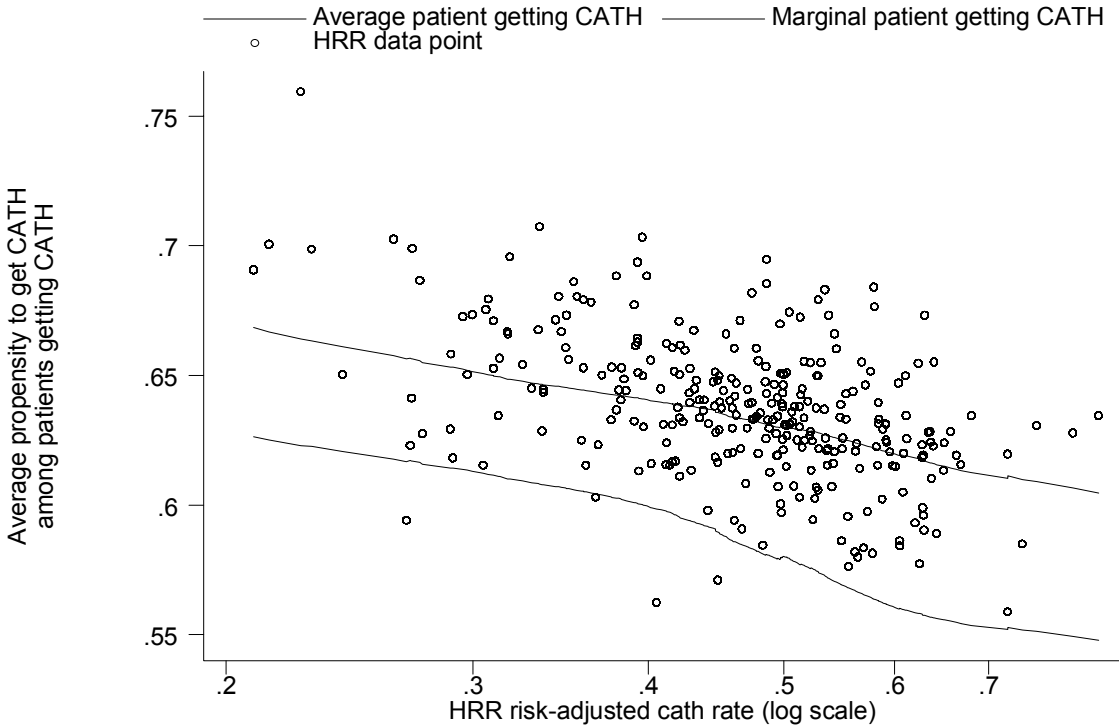| Sample:	IV Estimates of		
	Impact of CATH:		**Impact of $1000:**
	on 1-Year Survival	**on 1-year Cost ($1000s)**	**on 1-year Survival**
1. All patients	0.142	9.086	0.016
(n=129,895)	(0.036)	(1.810)	(0.005)
2.By CATH propensity			
a. Above the Median	0.184	4.793	0.038
(n=64,799)	(0.034)	(1.997)	(0.017)
b. Below the Median	0.035	17.183	0.002
(n=65,096)	(0.083)	(3.204)	(0.005)
Difference:	0.149	-12.39	0.036
	(0.090)	(3.775)	(0.018)
3. By age			
a. 65-80	0.171	6.993	0.024
(n=89,947)	(0.037)	(1.993)	(0.009)
b. Over 80	0.016	16.026	0.001
(n=39,948)	(0.108)	(2.967)	(0.007)
Difference:	0.155	-9.033	0.023
	(0.114)	(3.574)	(0.011)

Notes: CATH propensity is an empirical measure of patient appropriateness for intensive treatments. We define this measure by using fitted values from a logit model of the receipt of cardiac catheterization on all the CCP risk-adjusters. Differential-distance (measured as the distance between the patient's zip-code of residence and the nearest catheterization hospital minus the distance to the nearest hospital) is the instrument. Each model includes all the CCP risk-adjusters and the standard errors are clustered at the level of each HRR.

Table 2: Relationship Between Differential-Distance and Probability of Catheterization and Survival, and Differential-Distance and Observable Characteristics

Sample:	30-day CATH rate		1-year Survival		1-year Predicted Survival		30-day predicted CATH rate for patients getting CATH	
	DD Below Median	DD Above Median	DD Below Median	DD Above Median	DD Below Median	DD Above Median	DD Below Median	DD Above Median
All patients (n=129,997)	48.9%	42.8%	67.6%	66.7%	67.5%	67.2%	63.3%	63.2%
By CATH propensity								
Above the Median (n=64,733)	74.0%	67.1%	84.6%	83.8%	83.4%	83.5%	72.6%	72.6%
Below the Median (n=65,244)	22.9%	19.5%	50.1%	50.4%	51.1%	51.6%	32.3%	32.5%
By age								
65-80 (n=90,016)	61.1%	54.9%	74.3%	73.5%	73.9%	73.9%	67.4%	67.3%
Over 80 (n=39,961)	20.3%	16.5%	52.1%	52.1%	52.6%	52.7%	34.6%	34.1%

Notes: CATH propensity is an empirical measure of patient appropriateness for intensive treatments. We define this measure by using fitted values from a logit model of the receipt of cardiac catheterization on all the CCP risk-adjusters. Differential-distance (measured as the distance between the patient's zip-code of residence and the nearest catheterization hospital minus the distance to the nearest hospital) is the instrument. Each model includes all the CCP risk-adjusters and the standard errors are clustered at the level of each HRR.

Table 3: Relationship between the Average and Marginal Patient Receiving Cardiac Catheterization

Patient Characteristic	Characteristic of average patient getting CATH across all areas	Difference Between average patient and marginal patient getting CATH in higher-CATH HRRs
1. CATH propensity	0.633 (0.002)	-0.045 (0.008)
2. Over age 80	0.125 (0.002)	0.063 (0.012)
3. Not eligible for CATH using ACC/AHA guidelines	0.028 (0.001)	0.010 (0.003)

Notes: CATH propensity is an empirical measure of patient appropriateness for intensive treatments. We define this measure by using fitted values from a logit model of the receipt of cardiac catheterization on all the CCP risk-adjusters. Sample is restricted to patients receiving cardiac catheterization within 30 days of an AMI. ACC/AHA guidelines reflect a binary variable assigned to each patient in the CCP that measures whether the patient is ideal, appropriate, or not eligible for catheterization based on chart-review.

Table 4: Correlation of HRR Level Measures of Intensive Treatment, Medical Management, Support of Medical Treatment and Demographic Characteristics

HRR indicator	Mean	SD	10th percentile	90th percentile	Correlation with HRR CATH rate
Measures of intensive treatment					
Risk-adjusted 30-day CATH rate	46.3%	9.1%	34.5%	58.3%	**1.00**
Interventional Cardiologist per 100,000	2.43	0.78	1.30	3.40	**0.56**
Risk-adjusted 30-day PTCA rate	17.7%	5.1%	11.3%	23.6%	**0.81**
Risk-adjusted 30-day CABG rate	13.4%	2.9%	10.2%	16.9%	**0.51**
Risk-adjusted 12-hour PTCA rate	2.7%	2.6%	0.6%	5.8%	**0.52**
Measures of medical management					
Risk-adjusted β-blocker rate	45.6%	9.5%	34.2%	58.3%	**-0.31**
Non-interventional Cardiologists per 100,000	2.23	1.60	0.60	4.60	**-0.29**
Support for intensive treatment					
Cardiovascular Surgeons per 100,000	1.06	0.27	0.70	1.40	**0.33**
Cath Labs per 10,000	2.40	0.76	1.50	3.30	**0.39**
Demographic characteristics					
log of resident population	13.96	0.89	12.72	15.18	**-0.05**
log of per capita income	9.55	0.20	9.31	9.85	**0.02**
Percent College graduates	19.3%	5.5%	13.1%	26.6%	**-0.05**

Notes: HRR surgical and medical intensity rates are computed as the risk-adjusted fixed effects from a patient level regression the receipt of CATH or beta-blockers on HRR fixed effects and CCP risk-adjusters. CATH propensity is an empirical measure of patient appropriateness for intensive treatments. We define this measure by using fitted values from a logit model of the receipt of cardiac catheterization on all the CCP risk-adjusters.

Table 5: Relationship between HRR Patient Characteristics and HRR Treatment

HRR-Level Independent Variables:	HRR Level Dependent Variables			
	Risk-adjusted 30-day CATH rate	Risk-adjusted 30-day CATH rate	Risk-adjusted Beta Blocker Rate	Risk-adjusted Beta Blocker Rate
Average propensity to get CATH	0.707 (0.248)	0.761 (0.239)	-0.753 (0.306)	-0.590 (0.205)
Percent under age 65		0.253 (0.193)		-0.534 (0.199)
log of resident population		-0.006 (0.008)		-0.009 (0.009)
log of per capita income		0.031 (0.034)		0.209 (0.031)
R-squared	0.04	0.05	0.04	0.21
N	303	303	303	303

Notes: HRR surgical and medical intensity rates are computed as the risk-adjusted fixed effects from a patient level regression the receipt of CATH or beta-blockers on HRR fixed effects and CCP risk-adjusters. CATH propensity is an empirical measure of patient appropriateness for intensive treatments. We define this measure by using fitted values from a logit model of the receipt of cardiac catheterization on all the CCP risk-adjusters.

Table 6: Instrumental Variable Estimates of Intensive Management and Spending on Survival, by Surgical Intensity of Hospital Referral Region

| | IV Estimates of | | |
| | Impact of CATH: | | Impact of $1000: |
Sample:	on 1-Year Survival	on 1-year Cost ($1000s)	on 1-year Survival
1. By HRR risk-adjusted CATH rate			
a. Above the Median	0.256	6.691	0.038
(n=63,771)	(0.061)	(3.510)	(0.021)
b. Below the Median	0.09	9.835	0.009
(n=66,124)	(0.059)	(3.155)	(0.007)
Difference:	0.166	-3.144	0.029
	(0.085)	(4.720)	(0.022)
2. By HRR risk-adjusted β-blocker rate			
a. Below the Median	0.189	6.33	0.03
(n=64,862)	(0.050)	(2.434)	(0.013)
b. Above the Median	0.071	11.003	0.006
(n=65,033)	(0.048)	(2.550)	(0.005)
Difference:	0.118	-4.673	0.024
	(0.069)	(3.525)	(0.014)

Notes: HRR intensity rates are computed as the risk-adjusted fixed effects from a patient level regression the receipt of CATH or beta-blockers on HRR fixed effects and CCP risk-adjusters. Differential-distance (measured as the distance between the patient's zip-code of residence and the nearest catheterization hospital minus the distance to the nearest hospital) is the instrument. Each model includes all the CCP risk-adjusters and the standard errors are clustered at the level of each HRR.

Table 7: Relationship Between HRR Catheterization Rate, Survival and Costs, by Clinical Appropriateness for Intensive Management

	OLS Estimates of the Relationship Between HRR Risk-Adjusted CATH Rate and:			
Sample:	**1-Year Survival**	**1-year Cost ($1000s)**	**Beta Blocker in Hospital**	**Catheterization within 30 days**
1. All patients	0.007	8.093	-0.28	0.702
(n=138,873)	(0.019)	(1.410)	(0.073)	(0.004)
2. By CATH propensity				
a. Top Tercile	0.052	10.012	-0.366	0.802
(n=46,287)	(0.019)	(1.439)	(0.073)	(0.032)
b. Middle Tercile	0.03	11.154	-0.271	0.906
(n=46,295)	(0.030)	(1.784)	(0.082)	(0.021)
c. Bottom Tercile	-0.075	2.763	-0.209	0.369
(n=46,291)	(0.028)	(1.612)	(0.073)	(0.021)
Difference (Top-Bottom):	0.127	7.249	-0.157	0.433
	(0.034)	(2.161)	(0.103)	(0.038)
3. By age				
a. 65-80	0.023	9.616	-0.311	0.775
(n=96,093)	(0.021)	(1.448)	(0.072)	(0.012)
b. Over 80	-0.031	4.738	-0.215	0.531
(n=42,780)	(0.028)	(1.603)	(0.080)	(0.022)
Difference (Top-Bottom):	0.054	4.878	-0.096	0.244
	(0.035)	(2.160)	(0.108)	(0.025)
4. By AHA/ACC criterion				
a. Ideal	0.027	9.845	-0.302	0.769
(n=89,569)	(0.023)	(1.599)	(0.076)	(0.010)
b. Appropriate	-0.002	6.174	-0.282	0.752
(n=31,800)	(0.024)	(1.537)	(0.080)	(0.026)
c. Not appropriate	-0.08	2.958	-0.177	0.264
(n=17,504)	(0.040)	(1.511)	(0.065)	(0.021)
Difference (Top-Bottom):	0.107	6.887	-0.125	0.505
	(0.046)	(2.200)	(0.100)	(0.023)

Notes: CATH propensity is an empirical measure of patient appropriateness for intensive treatments. We define this measure by using fitted values from a logit model of the receipt of cardiac catheterization on all the CCP risk-adjusters. HRR surgical and medical intensity rates are computed as the risk-adjusted fixed effects from a patient level regression the receipt of CATH or beta-blockers on HRR fixed effects and CCP risk-adjusters.

Table 8: Relationship between Survival and alternative measures of HRR size, by clinical appropriateness of patient

HRR-Level Independent Variables:	All patients	By CATH propensity			All patients	By CATH propensity		
		Top Tercile	Middle Tercile	Bottom Tercile		Top Tercile	Middle Tercile	Bottom Tercile
Risk-adjusted CATH rate	0.006	0.052	0.031	-0.077	0.008	0.053	0.031	-0.075
	(0.019)	(0.019)	(0.030)	(0.028)	(0.019)	(0.019)	(0.030)	(0.028)
log of resident population	-0.002	-0.001	0.002	-0.007				
	(0.002)	(0.002)	(0.003)	(0.003)				
log of AMIs per hospital					0.005	0.014	0.006	-0.007
					(0.004)	(0.005)	(0.007)	(0.006)
N	138,873	46,287	46,295	46,291	138,873	46,287	46,295	46,291