CHAPTER TWO

Causes and Consequences of Regional Variations in Health Care[1]

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Contents

Abstract

There are widespread differences in health care spending and utilization across regions of the US as well as in other countries. Are these variations caused by demand-side factors such as patient preferences, health status, income, or access? Or are they caused by supply-side factors such as provider financial incentives, beliefs, ability, or practice norms? In this chapter, I first consider regional health care differences in the context of a simple demand and supply model, and then focus on the empirical evidence documenting causes of variations. While demand factors are important—health in

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particular—there remains strong evidence for supply-driven differences in utilization. I then consider evidence on the causal impact of spending on outcomes, and conclude that it is less important how much money is spent, and far more important *how* the money is spent—whether for highly effective treatments such as beta blockers or anti-retroviral treatments for AIDS patients, or ineffective treatments such as feeding tubes for advanced dementia patients.

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JEL Codes: I100; I110; I120; I180; R120

1. INTRODUCTION

A recently published Atlas documented dramatic differences in the utilization of an important health input. Relative to the rates observed in the Boston area, utilization was 74 percent higher in New Haven and more than 200 percent higher in San Francisco.[2] One might explain differences in utilization by variations in income, health status, or prices, yet these factors do not appear to explain away the wide variations we observe. So why have these patterns—in per capita consumption of *meat and poultry*, ranging from 31 pounds in the Boston region to 113 pounds per capita in the San Francisco region—not received more attention from health experts or health economists?

In this chapter, I attempt to distinguish between the admittedly puzzling geographic variation in meat and poultry consumption and geographic variation in health care utilization. There are certainly many reasons why regional variations in utilization can be justified by underlying health status, preferences and income, or productivity differences among providers—surgical rates should be higher in regions where surgeons get better results (Chandra and Staiger, 2007). But there are also reasons why such variations might not be efficient. We know that specific components of the health care industry, such as the widespread use of insurance with modest co-payments, leads to the twin problems of moral hazard and adverse selection. And beginning with Arrow (1963), economists have argued that many of the unique features and institutions associated with medical care—ranging from not-for-profit ownership to licensure of providers to the structure of insurance—are best understood as the result of "uncertainty in the incidence of disease and in the efficacy of treatment" (Arrow, 1963, p. 941).

[2] http://maps.ers.usda.gov/FoodAtlas/

Health care is not the only sector of the economy with these characteristics—car repair, home construction, and management consultancies exhibit uncertainty about the efficacy of the fix, even if they are not typically insured to the same degree. While regional variations surely exist in the quality and cost of automotive repairs, it is less likely that the government would propose accountable car repair organizations, for example.

Regional variations in health care are different, for at least two reasons. First, assuming that the variation we observe is "unwarranted" in the sense that it cannot be explained by legitimate causes such as health status, the magnitude of variation is so large that the potential gain from erasing such inefficiencies—3 percent of GDP or more in the United States—is worth pursuing. And second, these inefficiencies are unlikely to be shaken out by normal competitive forces, given the patchwork of providers, consumers, and third-party payers each of which faces inadequate incentives to improve quality or lower costs (Fuchs and Milstein, 2011).

Following on the earlier survey by Charles Phelps in the Handbook (Phelps, 2000), this review considers five general questions in reflecting on the economics of regional variations in health care. First, what are the *theoretical* causes of such differences? Traditionally, the presence of regional variation in medical care utilization has been viewed through the lens of "supplier-induced demand," the idea that regional variations can be explained by the utility-maximizing behavior of health care providers responding to a fee-for-service environment and relative scarcity (or abundance) of providers (McGuire, 2011). The problem arises when individual physicians in two seemingly similar regions—with identical insurance mechanisms and similar patients—end up providing much different quantities of health care. That is, standard supplier-induced demand models may argue that physicians do more for their patients than is optimal, but does not typically explain why physicians in McAllen, TX, do so much more for their Medicare patients than those in El Paso (Gawande, 2009). To address these issues, I adopt a model based on Chandra and Skinner (2011) and Wennberg et al. (2002) to parse out both supply and demand factors that might be expected to explain regional variation in specific types of treatment, ranging from highly effective care that clearly saves lives at minimal cost (such as beta blockers for heart attack patients) to very expensive treatment without known benefits for patients (like proton beam therapy for prostate cancer).

Second, I use this basic framework to consider the empirical evidence on *causes* of geographic variation in health care utilization and expenditures. This is the key section to assess the evidence on whether supply-side variations really do exist. If all of the regional variation in observed utilization rates can be explained by other factors such as patient preferences, relative prices, income, and health, then the puzzle of regional variations is not even a puzzle any more. I focus in this chapter largely on

US regional variations, but document also a growing literature reflecting international variations both within and across countries.[3]

Third, what are the *consequences* of higher health care spending? Does more spending yield better outcomes—or is how the money spent more important for health? A key focus of this section is to understand how geography might be used as a statistical instrument in health economics to help estimate whether greater intensity of care is associated with better health outcomes. Starting with the early work by Glover (1938) and Wennberg and Gittelsohn (1973), and continuing through the more formal analysis using instrumental variables, there has been a long-standing tradition of using geography as an instrument to make inferences about the health care "production function"(Fisher et al., 2003b; McClellan et al., 1994). Some studies have suggested a negative association between spending and outcomes, while others have found a positive association, but what is most striking is how much variability there is in outcomes across providers or regions, and how poorly such variability is associated with factor inputs.

Fourth, what are the policy implications of observing variations in health care utilization? If there are enormous variations in the productivity of concrete, a seven-digit SIC code output with readily apparent quality measures (Syverson, 2004), is it any surprise that there are even greater disparities in the productivity of health care across regions or hospitals where outputs are difficult to measure and rarely made public? The sometimes slow diffusion of valuable and highly efficient medical innovations, as in Phelps (2000), has strong parallels with the slow diffusion of knowledge observed across countries (Eaton and Kortum, 1999; Skinner and Staiger, 2009), yet the practical challenges of how to "fix" such slow diffusion rates across regions (or countries) are still being debated.

Finally, while there are regional variations in health care utilization, there are also strong gradients across the US in health (Kulkarni et al., 2011), and the two appear only incidentally correlated (Fuchs, 1998). Explaining variations in health is perhaps even more important, and suggests a greater focus on factors other than medical care that may have a more direct impact on health, such as regional variation in the per capita consumption of beef and poultry.

2. AN ECONOMIC MODEL OF REGIONAL VARIATIONS IN HEALTH CARE

Economic models typically include a demand and supply side, and so I adopt a simple model from Chandra and Skinner (2011) to characterize each side of the market.

[3] For a useful bibliography of such studies, see WIC (2011).

2.1. The Demand Side

The demand side, based on Hall and Jones (2007) and Murphy and Topel (2006), is a simplified two-period model of consumption and leisure where the individual's perceived quality of life, $s(x)$, is in turn influenced by medical spending x:

$$V = U(C_1) + \frac{s(x)U(C_2)}{1+\delta} \tag{2.1}$$

where C_i is consumption in period i, δ is the discount rate, and x measures health care inputs.

Assume the expected survival or quality of life function is concave, so that $s'(x) \geq 0$, $s'' < 0$. The Grossman model includes a variety of different approaches that individuals may improve their health "stock" but in this simplified model the demand for health is expressed solely through the demand for x (Grossman, 1972). Utility is maximized subject to the budget constraint:

$$Y_1 + \frac{Y_2}{1+r} - P = C_1 + px + \frac{C_2}{1+r} \tag{2.2}$$

where Y_i is income or transfer payments in period i, p the consumer price of health care, P the premium (or tax) paid for insurance, and r is the interest rate. Assume that x is measured in units of what one dollar in real resources will purchase, meaning that the true or social cost (q) per unit of x is normalized to one, but where the patient pays p. (Thus if the coinsurance rate is 20 percent, $p = 0.2$.) This demand-side model is straightforward, even if the assumptions implicit in this model can sometimes be at odds with the empirical evidence.[4]

Maximizing the utility function (2.1) subject to (2.2), and rearranging yields the optimality condition:

$$\Psi = \frac{U(C_2)}{(1+\delta)\frac{\partial U}{\partial C_1}} = \frac{p}{s'(x)} \tag{2.3}$$

Let Ψ be individual demand for an extra quality-adjusted year of survival, which could in theory vary across regions for a variety of reasons: higher income, for example, implies a lower marginal utility of first-period consumption and hence a much higher demand for health care. Differences in the curvature of the utility function

[4] For example, because demand is a function of the inverse of the marginal utility of first-period consumption, when the Arrow—Pratt risk aversion parameter is 3 (or the intertemporal elasticity of substitution is 1/3), doubling consumption increases demand and leads to 2^3 times the demand for health care (Murphy and Topel, 2006). As Hall and Jones explain, the marginal utility of a third flat-screen TV falls rapidly relative to the demand for the ultimate luxury good—health (Hall and Jones, 2007). Yet we do not typically observe such large income elasticities at a point in time.

(and hence risk aversion) and the time preference rate can further affect the trade-off between current consumption and future health.

2.2. The Supply Side

I assume that physicians seek to maximize the perceived value of health for their patient, given by $\Psi s(x)$, subject to financial considerations, resource capacity, ethical judgment, and patient demand (Chandra and Skinner, 2011). While there are dishonest physicians that belie this assumption, it is at least consistent with the majority of physician behavior. In this simple model, physicians act as price takers, but may still face a wide array of different prices paid by private insurance, Medicare, and Medicaid, for the identical procedure. This model therefore misses the complexity of markets in which hospital groups and physicians jointly determine quantity, quality, and price (Pauly, 1980).

Physicians also care about the income they make. For simplicity, let income be represented by $R+\pi x$, where R is the physician's salary and π measures the net revenue arising from the procedure (or more generally, the vector of different procedures) x. Note that the price paid by the patient, p, could be quite different from the profitability of the procedure, π, and that when the provider is paid less than marginal cost, then $\pi > 0$, but when the procedure is profitable, $\pi < 0$.

Thus the health care provider is assumed to maximize the sum $\Psi s(x) + \Omega(R+\pi x)$, where Ω is a function that captures the trade-off between the physician's desire to improve the value of patient survival and her own income. But the provider may still be constrained by factors such as capacity constraints (a lack of available hospital beds, so that $x \leq \boldsymbol{X}$, where $\boldsymbol{X}$ is the local hospital bed supply) or ethical judgment (the treatment is not worth the social cost or the patient is not better off as a consequence when $s'(x)$ is small or even negative and out-of-pocket expenses are high); these additional restrictions are reflected in a portmanteau constraint μ.[5] In this simplified case, the optimality condition for the provider can be written as

$$\Psi s'(x) = -\omega\pi + \mu \equiv \lambda \tag{2.4}$$

where ω is the derivative of Ω with respect to x, or the marginal value of an extra dollar of income, and the combination of constraints is summarized by the shadow price λ. For example, if financial incentives to do more (that is, $-\omega\pi < 0$) are in turn offset by ethical standards to "do no harm" to patients ($\mu = \omega\pi$), so that $\lambda = 0$, then physicians seeking to do the best for their patients would drive $s'(x)$ to zero.

Consider Figure 2.1, showing both $\Psi s'(x)$ and λ.[6] Note also the key assumption that patients are sorted in order from most appropriate to least appropriate for

[5] See Chandra and Skinner (2011) for a complete derivation of the model.

[6] Note that λ could vary with x; for simplicity it is held constant.

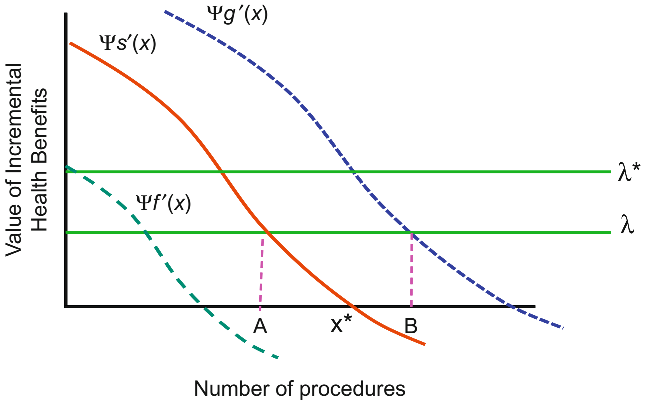


Figure 2.1 Marginal productivity of health outcomes, for different production functions and constraints.

treatment, thus describing a downward sloping $\Psi s'(x)$ curve (Baicker et al., 2006). The equilibrium occurs where, as in equation (2.4), $\Psi s'(x) = \lambda$, or at point A in Figure 2.1. In most health care systems λ will generally not be equal to the social cost of an additional unit of x, equal to one; typically capacity constraints would lead to $\lambda > 1$, and the existence of insurance (and hence $p < 1$) would push λ below 1; either condition leads to static inefficiency.

How can this model be used to explain regional variations? Consider two general classes of variations across regions. The first is that all physicians and hospitals are subject to the same $s(x)$ production function, but that regional variation in utilization occurs because of movements along the $s'(x)$ curve because of variations in λ to (say) $\lambda^\star$ as in Figure 2.1. Examples of such movements would include:

(a) Marginal financial incentives (variations in π) arising from differences across regions in reimbursement rates and prices for procedures—more of an issue perhaps for Medicaid and private insurance than for Medicare, where prices are fixed, albeit with rough adjustments for differences in cost of living and other factors (IOM, 2011). More generally, physicians may differ across regions with regard to their sensitivity towards financial incentives, as summarized by the marginal utility of income ω. For example, Gawande (2009), in trying to explain why Medicare spending was so much higher in McAllen, Texas, compared to El Paso, emphasized the more "entrepreneurial" characteristics of physicians in McAllen—that is, an increased sensitivity to profitable activities, or a larger ω.

(b) Capacity or ethical constraints that reflect quasi-fixed factors in the region (showing up as μ), for example the density of catheterization laboratories, specialists, hospital and ICU beds, and diagnostic imaging facilities (for example, an MRI down the hall from the physician's office). This is the mechanism that, as we discuss below, underlies the idea of "supply-sensitive" or Category III care, that the shadow price of the extra bed-day is so low because there are empty beds.[7] These differences in quasi-fixed capacity may in turn arise from historical accidents; in contrast to New Haven, for example, there were a larger number of religious groups establishing hospitals in Boston (Wennberg, 2010).

(c) Patient price or access. If most patients are uninsured and facing full dollar cost, or if they tend to be wary of surgical procedures, then the physician is assumed to account for their higher costs and avoid marginally valuable treatments. Conversely, if it takes a long time for patients to get to the clinic or hospital, or they face high implicit costs of doing so, then x will be lower (and $s'(x)$ higher).

(d) Malpractice risk, which changes the implicit costs or benefits of performing the procedure. In some cases, "defensive medicine" can work to reduce λ and increase utilization: the CT scan to provide cover for sending a patient home from the emergency room or the PSA test to avoid lawsuits in the event that the patient is later diagnosed with prostate cancer (King and Moulton, 2006). In other cases, malpractice concerns may increase the implicit costs if by performing the procedure the physician puts herself at greater risk of a lawsuit (Baicker et al., 2007; Currie and MacLeod, 2008).

Recall that all these variations in capacity, financial incentives, and so forth would lead to different points along the same production function. Thus if all regions were on the same production function $s(x)$, the cross-sectional association across regions between spending and outcomes should trace out the production function and hence the marginal "value" of health care spending. If regions also differ with regard to their production function $s(x)$, as is argued below, then these cross-regional comparisons will no longer trace out $s(x)$ over ranges of x, but some combination of both variation in the production function and variation in λ. As I argue below, this creates difficulties in interpreting regression coefficients seeking to answer the question "is more better?"

A second approach to explaining geographic variations arises by allowing the production function to differ across regions or physicians. Most obviously, this will occur because of differences in health status; Lafayette, LA, has more underlying disease burden than Hawaii, so we might expect the physician production function in Lafayette to look more like $f(x)$ than $s(x)$ in Figure 2.1—there is most likely no amount of health care spending that will make Lafayette as healthy as Hawaii. As well, one would expect that for any given x, $f'(x) > s'(x)$.

A more interesting reason for variations in the production function—shifted from $s(x)$ to $g(x)$ in Figure 2.1—is that physicians may have adopted more effective

[7] This also begs the question of why a particular region might have so much capacity to begin with; capacity can best be described as predetermined rather than exogenous. One study did find evidence that hospital beds are less likely to move than people; thus regions subject to out-migration tend to have the greatest supply of beds (Clayton et al., 2009).

innovations with small costs, such as checklists for surgeries or beta blockers for heart attacks, thus enhancing the productivity of a given level of inputs x (de Vries et al., 2010; Skinner and Staiger, 2009). Similarly, physicians may also be more skilled at a specific procedure for people with similar health status. For example, in one study of heart attack patients, patients experienced better outcomes from cardiac interventions in regions with higher rates of surgery, consistent with a Roy model of labor market sorting (Chandra and Staiger, 2007). Other explanations for such differences rely also on systematically different organizational structures of practices (de Jong, 2008).

Physicians may also be overly optimistic (as in $g'(x)$ in Figure 2.1) or pessimistic ($f'(x)$) about their ability in performing procedures, or more generally about the marginal effectiveness of specific treatments. For example, arthroscopic surgery to treat osteoarthritis of the knee was a common procedure in the early 2000s, with 650,000 performed annually at a cost of about $5,000 each. In this procedure, surgeons enter the joint area with tiny instruments, and clean out the joint while removing loose particles. In 2002, a randomized study of this procedure was conducted, with "sham" surgery performed on the control group (Moseley et al., 2002). No benefit was found relative to the control group, suggesting that, prior to the study's publication, the perceived surgical production function was to the right of the true production function in Figure 2.1.

Alternatively, physicians may not understand that in treating a patient for a specific disease, their prescription drug may interact with others already prescribed by other providers (Zhang et al., 2010b), reflecting the problem that networks become increasingly complex with more specialists involved (Becker and Murphy, 1992). In either case, one can end up with different regions operating on different production functions, with vastly different approaches to treatments, even though patients may not be aware that they are receiving more or less intensive care (Fowler et al., 2008).

What about the interaction between supply and demand? After all, every one of the 650,000 patients annually undergoing arthroscopic knee surgery (prior to 2002) agreed to the procedure, which even in the absence of out-of-pocket costs involved pain and lost time for recovery. Presumably the patient formed beliefs of her marginal benefit in part based on the physician's expertise, and so the perceived demand for the procedure would depend on physician advice. This is not "supplier-induced demand" *per se*; after all, it is the physician's job to convey expert information about the incremental benefits of the procedure to the patient. But given the spectrum of opinions held by physicians across regions (Sirovich et al., 2005), it should not be surprising if variations in physician opinions are mirrored by variations in patient beliefs across regions.

Less well understood is why patients sometimes appear to hold a more optimistic view of the marginal benefits of treatment than even their physician. For example, the COURAGE trials for patients with stable angina showed that stents, wire-mesh cylindrical devices inserted in narrowing cardiac arteries to improve blood flow, provided no

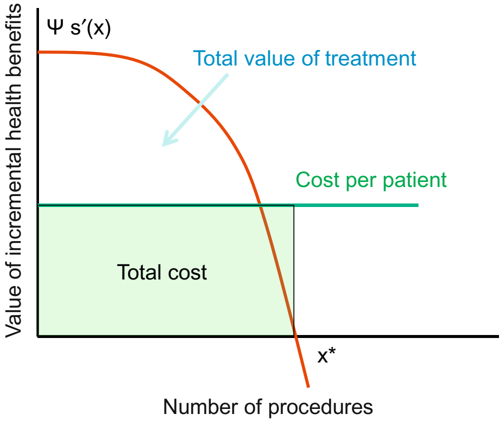


Figure 2.2 Benefits (area under the curve) and costs of effective (category i) innovation. *Source: Chandra and Skinner (2011).*

survival or heart-attack benefit to their patients, although it did reduce pain and improve functioning modestly for several years (Boden et al., 2007). In a matched survey of patients and physicians, physicians in one teaching hospital understood this evidence from the COURAGE trial. By contrast, their patients believed, falsely, in the protective effects of a stent against early death and heart attacks (Rothberg et al., 2010b).

Another way in which the traditional demand model falls short is where patients are observed to use too little of high-value drugs such as anti-hypertensives, suggesting an absurdly low value placed on their own life (Chandra et al., 2010). Indeed, even when the monetary price is zero or even negative (Volpp et al., 2008), utilization of effective treatments is below what it should be, raising questions of whether behavioral models of demand are better descriptions of behavior. Still, it seems unlikely that such anomalies in behavior should explain *regional* variations in demand.

In considering the empirical evidence, I will attempt to distinguish between the λ-based variation, which may reflect both supply- and demand-side factors, and variations in actual or perceived production functions (or marginal productivity measures), as has been found in other non-health care industries (Syverson, 2011).

2.3. A Typology of Health Care Services

I follow Wennberg et al. (2002) and Chandra and Skinner (2011) in considering three broad categories of health care inputs. The first is for highly effective treatments such as antibiotics for infections, beta blockers for heart attack patients, or a splint for a broken bone. These effective (or Category I) treatments are either productive across a wide swath of individuals, but very low cost—for example, aspirin for heart attack patients—or are highly productive and expensive for a well-defined group of patients. For example, in Figure 2.2 the graph showing the marginal value of anti-retroviral

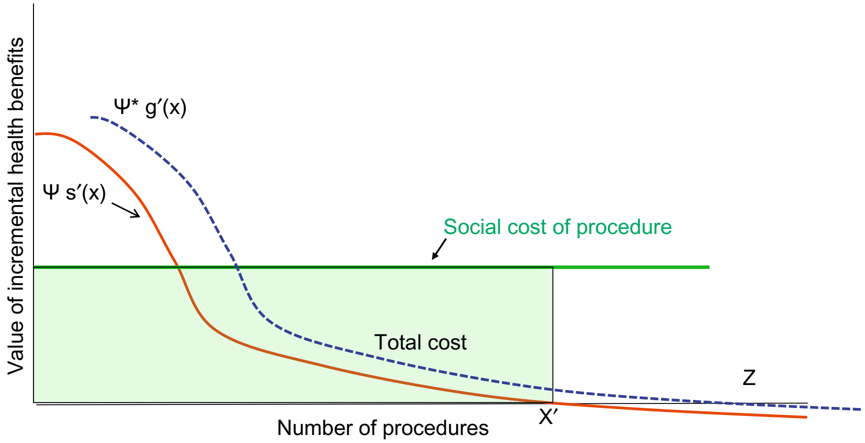


Figure 2.3 Benefits (area under the curve) and costs of category ii innovation. *Source: Fisher and Skinner (2010).*

treatments for HIV and AIDS patients. These are clearly beneficial (albeit very expensive) for those with the disease. But even when $s'(x)$ is driven to zero—that is, physicians do not worry about the high price but only give the drug to patients who would benefit—there is still little margin for overuse, because the side-effects are sufficiently serious to preclude widespread usage. Thus net value, or the area under the curve minus the cost (shown as the shaded rectangle in Figure 2.2), is still very large (Chandra and Skinner, 2011).

A second category of treatments exhibits considerable heterogeneity in benefits across different types of patients. One example is stents, where benefits are well established for patients who have very recently experienced a heart attack (Hartwell et al., 2005). These patients are shown on the left side in Figure 2.3, where benefits $\Psi s'(x)$ are considerably above social costs. But there is also a larger group of patients with more modest benefits. For example, the use of stents for the treatment of stable angina (compared to optimal medical management), as noted above, yields no improvement in mortality, no reduction in subsequent heart attacks, and a modest improvement in functioning over the next several years (Weintraub et al., 2008). Similarly, back surgery is effective for spinal stenosis, a type of back pain involving compression of the spinal cord or of nerves emanating from the spinal cord (Weinstein et al., 2008). But much less is known about its value for patients without any organic cause for the back pain, comprising the majority of those suffering from back problems, as shown by the flat region of the marginal benefit curve in Figure 2.3, where benefits are below social cost. And given the shape of $s'(x)$ as drawn in Figure 2.3, the overall benefits (the area under the curve to the left of X') are not much greater than the overall costs, given by the rectangle to the left of X' (Chandra and Skinner, 2011).

Figure 2.3 also shows that small changes in the marginal benefit curve could have a strong impact on demand when the incremental medical value of the treatment is small, at least relative to other options. For example, preferences could play an important role in tonsillectomy rates, or choosing between mastectomy (removal of the breast) and lumpectomy followed by radiation therapy for the treatment of breast cancer, given that the two options yield similar long-term prognosis. These preferences would affect the perceived value of the treatment ($g'(x)$ versus $s'(x)$ in Figure 2.3) or differences in income or demand more generally ($\Psi^\star$ versus Ψ) all could exert a large influence on overall unconstrained utilization (Z versus X' in Figure 2.3), particularly at a point where out-of-pocket costs are low or non-existent and physicians are well compensated for providing the treatment. To the extent that patient preferences, physician skills, or capacity constraints for these procedures might differ across regions, we might expect to find large differences in utilization rates across otherwise similar patients.

"Supply sensitive" or Category III variations are types of treatments where the evidence either points to very small or zero effects, such as arthroscopy of the knee, or where the benefits are simply not known. For example, there are a variety of treatments for prostate cancer, with wide variations in costs but no clear evidence of superiority for one type of treatment over another (Leonhardt, 2009). Category III treatments also reflect the importance of available resources such as intensive care unit (ICU) beds, hospital beds, specialists, and other "system"-level parameters, but where there's really no evidence on what is the right rate of ICU admissions among chronically ill patients. As noted above, capacity is reflected by variations in λ, but to the extent that capacity is in turn determined by the perceived value of specific procedures (e.g. $g(x)$ versus $s(x)$), then capacity constraints become endogenous across regions. Given the close association between overall Medicare expenditures and Category III utilization rates (e.g. Wennberg et al., 2002), these types of utilization are likely to play a large role in explaining overall spending differences across regions.

The next section provides a selected tour of the geographic variations literature in light of this model, although the question addressed at each stage is: What is the *regional* factor (and not simply idiosyncratic characteristics of physicians or patients) that might be expected to explain geographic variation in expenditures? In other words, it is not enough to find that (for example) physician practice varies dramatically across individual physicians even after controlling for health status of the patient (Phelps, 2000), since random variations among physicians would tend to cancel out when averaged over very large numbers of physicians in New York or Los Angeles. More interesting is what causes characteristics of patients and providers to be correlated systematically *within* regions.

3. EMPIRICAL EVIDENCE ON GEOGRAPHIC VARIATIONS IN EXPENDITURES AND UTILIZATION

By necessity, much of the evidence from the United States uses Medicare claims data for the over-65 population, which is the closest insurance program to universal health care in the US. Given that standard economic variables such as co-payment rates and deductibles are the same across regions in the Medicare program, Medicare utilization should in theory exhibit less variation than for the under-65 population where characteristics of insurance plans—particularly Medicaid benefits—vary broadly across the country. And while patterns from Medicare spending do not always generalize to the under-65 population, the elderly do consume a disproportionate fraction of health care spending, and growth in the Medicare program represents considerable financial risk for the future stability of US government finances.

3.1. Units of Measurement and Spatial Correlations

In the early 1990s, the Dartmouth group sought to characterize regional markets in preparation for what was supposed to have been Clinton-era health care reform. They used 1992/93 discharge data from the Medicare population to determine "catchment areas" for local hospitals, or "hospital service areas" (HSAs). There were 3,436 HSAs, which in turn were combined to create 306 "hospital referral regions" (HRRs) required to have at least one tertiary hospital providing cardiovascular and neurosurgical services. As in the 1973 Wennberg and Gittelsohn study, utilization was determined by residence (in this case zip code), and not by where the treatment was actually received. Thus treatments received in Minneapolis by a resident of Davenport, Iowa, would be assigned to the Davenport HRR, and not to Minneapolis. The 306 HRRs did not generally follow county or state boundaries, but instead reflected the actual migration patterns of Medicare patients, sometimes by following interstate highway routes. These definitions have not been changed since the original Dartmouth Atlas, published in 1996 (Wennberg and Cooper, 1996), which makes temporal comparisons straightforward, as the zip code-based crosswalks have been modified over time to preserve the same geographical boundaries. The temporal stability, however, means that regions may no longer be as sharply defined given secular changes in hospital market catchment areas.

Some studies have used state-level data, with the idea that some part of regional variations may be explained by differences in state policies such as nursing home bed-hold policies or Medicaid payments (Intrator et al., 2007). However, there is considerable variation within states, particularly large ones such as California, Texas, Florida, or New York. Another approach is to use county-level data, which provides a much larger sample of counties and the ability to match with other county data, for example from the Center for Disease Control's Behavioral Risk Factor Surveillance System (BRFSS) data on health and health behaviors. Still, county boundaries may be imperfect aggregations of where people actually seek their care, particularly in rural areas with small counties that do not have their own hospital.

An alternative is to create cohorts based on relative distance to specific hospitals, such as a 10-mile circumference, or based on relative distance to specific types of hospitals. For example, McClellan et al. (1994) considered heart attack patients living relatively near to, or far from, a hospital with a catheterization laboratory used to provide surgical treatment. Thus patient zip code was an instrument to predict whether the individual received surgical intervention for their heart attack, with the implicit assumption that unobservable health status was similar across zip codes.

Another approach is to avoid the use of zip codes altogether, but instead to create "physician—hospital networks" or cohorts of individual patients based on where they tend to seek care. For example, several studies created such networks using Medicare claims data by first assigning patients to the primary care physician who sees them the most, and then by assigning the physician to the hospital to which they are most loyal (Bynum et al., 2007; Fisher et al., 2007). That is, the Princeton-Plainsboro physician—hospital network comprises patients who see the set of physicians who in turn are most likely to admit to Princeton-Plainsboro, even if the patient has never been admitted to that (or any) hospital.[8] While these groups are no longer based on zip codes, they do provide measures of costs and quality at a potentially relevant decision-making unit, particularly for integrated delivery systems.

One key disadvantage of the Medicare claims data is the presence of Medicare-sponsored managed care plans (Medicare Advantage). These are capitated plans by which Medicare pays a fixed amount (adjusted by risk factors) to insurance companies to provide coverage for their enrollees. As such, claims data are unavailable for this group, yet in some regions of the country, roughly 40 percent are enrolled in Medicare managed care. While there are concerns that the population in these plans are systematically healthier than in the fee-for-service plans (Brown et al., 2011), there is less evidence that selection issues have introduced bias in estimated measures for the fee-for-service population, particularly when risk adjusters are specific to that same population.[9]

Finally, a methodological shortcoming for most of this literature, particularly in section 4, is the lack of accounting for spatial autocorrelation across regions. For

[8] Nearly every Medicare enrollee sees at least one doctor annually, meaning that few enrollees are unassigned. These networks are very similar to the structure of patient populations in "accountable care organizations" under the 2010 health care reform legislation in the US.

[9] One might be concerned that regions with rapid growth in Medicare Advantage would also experience above-average growth in per-capita fee-for-service expenditures as healthier patients risk-select into Medicare Advantage. However, unpublished data suggest that the change in Medicare Advantage enrollment across HRRs does not have much predictive power in explaining growth in fee-for-service spending, as one might expect.

example, when researchers run a regression with 306 HRRs, they implicitly assume independence; that the error term in the regression for Boston tells us nothing about the error term for Worcester. But as Ricketts and colleagues have shown, this assumption is demonstrably false (Ricketts and Holmes, 2007). Often, although not always, adjusting for spatial autocorrelation leads to wider confidence intervals; thus studies without such adjustments (including most of the Dartmouth studies) who find either negative or positive influences of spending on outcomes could be falsely rejecting the null of no effect.

3.2. Health Care Expenditures

Differences in expenditures across regions provides a first look at variations, as well as highlighting the magnitude of spending differences, at least in the Medicare claims data. Table 2.1 shows a select group of regions along with a set of measures corresponding to overall expenditures in Columns 1 and 2. Column 1 shows average per-capita Medicare expenditures adjusted for age, sex, and race for 2007. There are remarkable differences in expenditures across regions, from $6,196 in Grand Junction, CO, to $16,316 in Miami, FL, with a coefficient of variation equal to 0.18.[10] Indeed, Miami is something of an outlier, having been at the top of the list for expenditures per capita in every year since the Atlas began collecting data in 1992. The difference in Medicare expenditures across regions is considerably larger in present value terms; for Grand Junction versus Miami, the net difference in expected lifetime payout approaches $100,000 assuming a 3 percent growth rate in real expenditures and a 3 percent discount rate. Thus Medicare redistributes substantial amounts of money across regions—particularly as a fraction of a typical elderly person's lifetime wealth and income—even after controlling for income and taxes paid (Feenberg and Skinner, 2000).

3.2.1. Adjusting for Prices

One objection to comparing expenditures across regions is that Medicare pays more per procedure in high-cost cities than in low-cost rural areas. When Medicare pays its providers, it adjusts payments in several ways: (1) cost-of-living (using slightly different approaches for hospital payments versus physician payments), (2) the disproportionate-share program (DSH) which provides additional reimbursements for hospitals serving low-income patients, and (3) providing additional reimbursements (per DRG) to compensate for training medical and surgical residents. Following the earlier work by the Medicare Payment Advisory Commission (MedPAC, 2009), Gottlieb et al. removed these price differences by applying common national prices per diagnostic-related

[10] The coefficient of variation reported in Table 2.1 is the ratio of the standard deviation to the mean, weighted by the overall Medicare population in each region.

Table 2.1 Regional Variation in Utilization and Health: Selected Measures

Column/HRR	1	2	3	4	5	6	7	8	9
Year	**2007 Medicare Expenditures**	**2007 Medicare Expenditures (price adjusted)**	**2007 Mortality Rates (per 1,000)**	**2005 Hip Fractures (per 1,000)**	**1994/95 β Blocker Use (%) ideal pts**	**2007 Back Surgery (per 1,000)**	**2003 PSA Tests Age 80 + (%)**	**2007 End-of-Life ICU Days**	**2001–05 Last 2 yrs MD Visits**
Grand Junction, CO	6,196	6,283	4.58	7.47		5.9	9.0	1.4	38
Huntington, WV	8,634	9,269	6.38	8.73	46	2.8	12.0	2.0	59
New York, NY	12,190	9,691	4.37	6.30	61	2.0	27.0	4.0	88
Rochester, NY	6,613	6,923	5.50	6.99	82	3.4	5.3	2.1	45
Chicago, IL	10,369	9,782	4.70	6.70	36	2.5	13.7	7.4	81
San Francisco, CA	8,498	6,881	4.25	5.45	65	3.1	13.4	4.6	64
Los Angeles, CA	10,973	9,685	4.42	6.24	44	4.0	24.8	8.0	109
Seattle, WA	7,126	6,718	4.68	6.27	52	5.3	13.4	2.9	45
McAllen, TX	14,890	15,026	4.59	6.30	5	3.3	24.9	8.0	100
Miami, FL	16,316	15,971	4.96	7.27	52	2.5	30.4	10.7	106
Bend, OR	6,520	6,457	4.67	7.72	50	7.4	8.4	1.6	38
US average	**8,571**	**8,571**	**5.04**	**7.34**	**51**	**4.5**	**19.0**	**3.9**	**61**
Coefficient of variation	0.18	0.16	0.09	0.14	0.27	0.31	0.35	0.43	0.32
Correlation coefficient*	0.87	1.00	0.37	0.33	−0.24	−0.12	0.36	0.62	0.68

*With price adjusted per capita Medicare spending.
Sources noted in text.

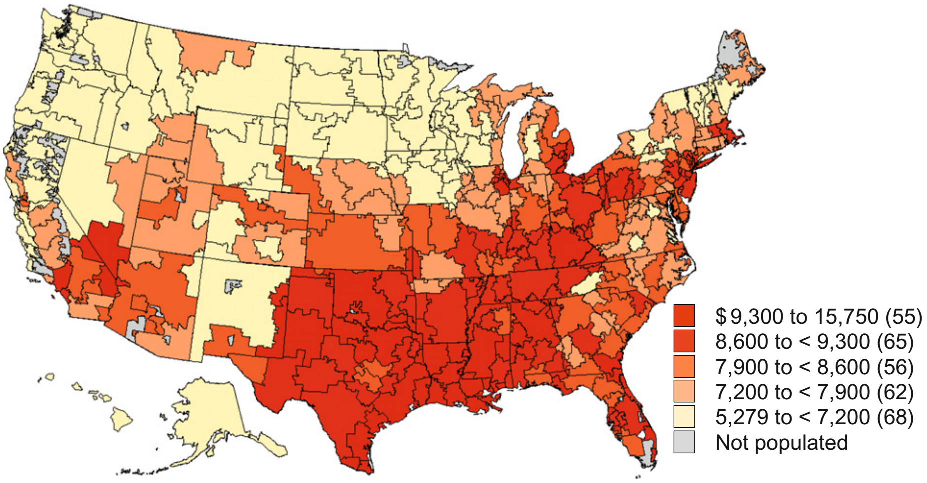


Figure 2.4 Price-adjusted per capita medicare expenditures 2007. *Dartmouth atlas of healthcare.*

group (DRG) weight for inpatient care, and resource-value unit (RVU) for outpatient care (Gottlieb et al., 2010). For other categories where quantity units were less apparent, such as outpatient care, they applied a wage-index adjustment.

These price-adjusted measures are shown in Table 2.1, Column 2.[11] Price adjustment had little impact on the two major outliers: McAllen, TX, and Miami. And not surprisingly, larger cities like San Francisco experienced a much larger drop in reported spending; it now becomes one of the lower-cost regions. On net, the population-weighted standard deviation in per capita expenditures declined modestly from $1,510 to $1,318; the correlation coefficient between the two measures is 0.87.

Price adjustment has perhaps the largest impact on expenditures for New York City (Manhattan), where per capita spending falls from $12,190 (unadjusted) to $9,691 (adjusted). The shift reflects not solely the wage index, but also the importance of graduate medical education subsidies for the large population of residents training in New York hospitals. Once adjusted for these differences in expenditures, however, they are only 13 percent above the national average. Table 2.1 and Figure 2.4 also illustrate the wide variation in overall expenditures even within states; Rochester, NY, on a price-adjusted basis, spends $6,923 per patient compared to $9,691 in New York City, and average spending in San Francisco is similarly nearly one-third below that in Los Angeles ($6,881 versus $9,685). The Pacific Northwest also tends to experience

[11] The price adjustment is normalized to the mean value of Medicare spending, $8,571 in 2007.

lower spending levels, with Seattle ($6,178) and Bend, OR ($6,457), among the lowest in the country.

3.2.2. Adjusting for Differences in Health Status

An immediate concern with these comparisons of spending is that the standard age–sex–race adjustment fails to adjust for health status. Bend, OR, may experience low levels of spending, but this may in turn reflect a healthier population who maintain exercise and healthy diets after retirement. In the context of the model, regions with poorer health status will experience greater incremental value of health care spending, such as $g'(x)$ compared to $s'(x)$ in Figure 2.1, leading to appropriate spending differences across regions (for the same λ) given different production functions of health, as shown by points A and B in Figure 2.1. Ideally, one would want to adjust for differences across regions in illness burden to ask the question of whether there is any regional variation left over that is not explained by health differences.

The most straightforward approach to risk adjustment is to consider mortality—a reliably measured marker of illness, particularly since simply being in one's last year of life predicts elevated spending. Huntington, West Virginia, is distinguished by one of the highest age–sex–race-adjusted Medicare mortality rates in the US: 6.32 percent compared to a US average of 5.12 percent, as shown in Table 2.1, Column 3.[12] Yet overall expenditures in Huntington, WV, are just 8 percent above average ($9,269). It may be that the larger share of lower-income households in Huntington experience worse access to care—fewer physicians in rural areas surrounding Huntington, for example. However, income *per* se (independent of health status) does not appear to explain regional variations in overall expenditures (Zuckerman et al., 2010), although other factors, such as rural location and local poverty, could have a larger impact on the supply of health care providers.

Note that mortality rates in the highest-expenditure regions, McAllen (4.47 percent) and Miami (5.12 percent), are below the national average. One could interpret this correlation in two ways. One is that these regions are in fact healthier than average, making their high level of health care spending all the more remarkable.[13] But a different interpretation reverses the causation: high spending in Miami and McAllen leads to better health and hence lower mortality rates. Strictly speaking, one cannot distinguish between these two hypotheses without estimating the causal effects of spending, discussed in section 4 below.

[12] These mortality estimates, from 2007, are for all Medicare enrollees, and not just those in the fee-for-service population.

[13] Recall that residence is determined by the zip code from the Medicare denominator file corresponding to the billing address. For snowbirds who travel back and forth between (say) McAllen and Rochester, NY, the billing address could be in either locale, but health care expenditures would be a weighted average of health care received in the two regions. Thus retirees would attenuate regional differences; McAllen's spending would be lower and Rochester's higher because of this assignment rule.

An alternative health risk factor is the rate of hospital admissions for hip fractures. Nearly every elderly person with a hip fracture is admitted to the hospital, and nearly every doctor agrees on the clinical criteria for hip fractures. Furthermore, hip fractures are largely determined by bone density, arising from early-life nutritional habits rather than current environment or health care services (Lauderdale et al., 1998). Huntington, WV, also experiences an elevated rate of hip fractures (8.73 per thousand), higher than the US average (7.34). Miami (7.27) and McAllen (6.30) are lower than average, with San Francisco among the lowest in the country (5.45). As discussed in section 6, variations in *health* are large (the coefficient of variation for hip fractures is 0.14), and not highly correlated with spending; the correlation coefficient between hip fracture rates and price-adjusted expenditures is 0.33.

Yet hip fracture captures only one dimension of underlying health status. The Medicare Current Beneficiary Survey (MCBS) includes self-reported health and disease prevalence (e.g. smoking, diabetes, obesity). Several studies have used the MCBS to show that at the micro level, variations in health status can explain at least some of the observed differences in expenditures across regions (Sutherland et al., 2009; Zuckerman et al., 2010). Zuckerman et al., for example, found that the gap between the highest and lowest spending quintiles shrank from about 52 percent without any price or illness adjustment to 33 percent after adjustment for patient reported illnesses such as diabetes, smoking, weight, and whether their doctor has told them they have any new diseases. On the one hand, these adjustments could understate true disease burden because of unobservable factors orthogonal to observed risk factors.[14] On the other hand, patients were asked what their physicians had recently told them, leading to a potential reverse causation: the more contact one has with the health care system, the more likely a diagnosis (Song et al., 2010).

A different approach is to use the risk-adjustment measures in the Medicare administrative file to elicit underlying health status (MedPAC, 2011). The advantage of this approach is the vast size of the database, and the ability to adjust every Medicare enrollee for risk factors. The Hierarchical Condition Coding (HCC) counts the number of different diagnoses that patients have received over the course of a year, and weight them for severity, with some diagnoses closely related to whether the patient had a specific procedure. Because the risk adjustment comes directly from the billing data (unlike the MCBS, which asks patients questions), it is even more likely to result in the "up-diagnosis" bias. For example, one study compared Medicare enrollees who moved to a high-intensity region with those moving to a low-intensity region (Song et al., 2010). Despite the sample being similar at baseline, those moving

[14] Recall that observed health factors will reflect the correlated component of unmeasured health factors; it is only the component of the unmeasured health factors that is orthogonal to observables that will cause trouble in interpreting results.

to a higher-intensity region experienced as much as 19 percent higher diagnosis rates.[15]

The problem of determining “true” risk adjustment is not simply an issue for measuring regional variations, but is a more general challenge when trying to compensate health care systems (or “accountable care organizations”) for treating sicker patients and for rewarding better risk-adjusted outcomes. The incentives become stronger to up-diagnose when institutions are paid on the basis of risk-adjusted costs and rewarded for above-average risk-adjusted outcomes.

A third approach is to use cohort measures of utilization, whether “backward-looking” cohorts that begin at (e.g.) the date of death and work backwards, or “forward-looking” cohorts that begin at the time of the heart attack or hip fracture.[16] The idea behind these measures is that people with a heart attack, or in their last six months of life, are more similarly ill whether in Huntington, WV, or Bend, OR. This may not hold, however—the decedent in Huntington may have had a host of complications that make her more expensive to treat. A hybrid approach considers cohorts, but performs additional risk adjustment, for example by only considering end-of-life cohorts with serious chronic illnesses, as in Wennberg (2008).

3.2.3. Adjusting for Income

Another possibility is that income explains differences across regions in expenditures, for example by shifting the marginal benefit curve $\Psi s'(x)$. (Recall that Ψ, the marginal dollar value of a life-year, is highly income elastic.) It is not entirely clear what would be the normative implications of a finding that high-income households are heavier users of Medicare—is it “warranted” or “unwarranted” variation given that Medicare is a publicly funded program? Certainly at the individual level, elderly people with lower education and income account for more Medicare expenditures in a given year (Battacharya and Lakdawalla, 2006; McClellan and Skinner, 2006; Sutherland et al., 2009), but these gradients conflate both income effects and health effects. Still, there is no evidence that individual income differences across regions explain more than a minor fraction of overall variation in regional Medicare expenditures for the US, particularly after controlling for health status (Sutherland et al., 2009; Zuckerman et al., 2010). On the other hand, strong positive associations between aggregate income

[15] Some papers used HRR-level or metropolitan region-level health and ethnicity characteristics to risk-adjust Medicare expenditures (Cutler and Scheiner, 1999; Rettenmaier and Saving, 2010; Skinner et al., 2005). The advantage of such variables is that they are typically well measured and include the kind of information one needs for unbiased risk adjustment, such as smoking rates. The disadvantage is these aggregated measures are more prone to the “ecological fallacy” problem. For example, the variable measuring percent Hispanic is highly significant and positive in HRR-level regressions. Yet at the individual level, there is no impact of Hispanic origin on spending. The discrepancy is explained by the large population of Hispanics in Miami, McAllen, and Los Angeles, regions where spending rates are also high (for both Hispanics and non-Hispanics).

[16] The “backward” and “forward” terminology is from Ong et al. (2009).

(and hence tax revenue) and health care spending are more the norm across states in the US Medicaid program, and in countries such as Italy (Mangano, 2010).

This section has demonstrated that there are sharp differences in both per capita expenditures across regions, with some of these differences attributed to prices being higher in urban areas, and differences across the country in health status—West Virginia and Louisiana have a larger burden of disease than Oregon and should be expected to spend more. While price adjustments are straightforward, adjusting for health is more difficult, and represents a balancing act between under- and overadjustment. Still, there is considerable residual variation in expenditures that cannot be explained away by these factors.

3.2.4. Regional Variation in Non-Medicare Expenditures

Earlier work from California has shown a strong correlation between utilization for the over-65 Medicare population, those covered by Medicare Advantage plans, and the under-65 population (Baker et al., 2008). Similarly, a recent study comparing Medicare utilization and private health insurance among larger employers who self-insure showed a correlation of about 0.6 between these private insurance individuals and Medicare utilization (Chernew et al., 2010b).

But there are other results that suggest much greater differences in the behavior of the under-65 and the Medicare markets. For example, Chernew et al. find a surprising *negative* correlation between under-65 expenditures (or prices times quantity) and Medicare spending. Nor was the wide gap in Medicare spending between McAllen and El Paso, TX, replicated in the under-65 Blue-Cross Blue-Shield population (Franzini et al., 2010), suggesting that private insurance may have more leverage in restricting high utilization rates (Philipson et al., 2010).

Transacted prices for health care are known to vary tremendously across regions and hospitals depending on market structure and concentration on the side of providers such as hospitals and physician groups, and payers such as insurance companies or large employers (Gaynor and Town, 2011). So the variability at a point in time in prices in the under-65 population may bear little relation to the cost per procedure (or cost per patient) in the over-65 population where prices are largely fixed.[17] Hospitals might be shifting costs from the Medicare market to the private market and vice versa, although a recent paper suggests that when hospitals feel pressure to constrain their costs they are able to do so (Stensland et al., 2010). Understanding this interaction between private insurance markets and Medicare is a topic for further research.

[17] Complicating things further, there is evidence that this association is changing over time; at the state level, the correlation between non-Medicare and Medicare spending declined from nearly 0.6 in 1991 to roughly −0.15 in 2004 (Rettenmaier and Saving, 2010).

One consistent finding is the lack of correlation between state-level Medicaid and Medicare spending (Cooper, 2009; Rettenmaier and Saving, 2010). This suggests that states with less generous Medicaid programs are shifting costs to federally supported Medicare. Because Medicare is a fixed-price mechanism, the only way to increase Medicare income is by providing more intensive care to the relatively well-compensated Medicare patients, a classic "supply-driven" response in which physicians do more (by working further down the appropriateness curve) for their Medicare patients, leading to a lower λ and hence more utilization.

Expenditures provide a good measure of the opportunity cost of health care spending, particularly when aggregated over large populations of Medicare enrollees. But expenditures are simply averages of different types of health care, some of which is highly valuable in improving health (Category I) and others much less so (Category III). It is therefore useful to consider geographic variation in the three categories of treatments separately.

3.3. Effective Care (Category I)

The 1999 Cardiovascular Atlas provided an early national perspective on regional variations in Category I treatments that are both highly cost effective and have clear clinical benefits (Wennberg and Birkmeyer, 1999). It drew on the Cooperative Cardiovascular Project (CCP), a comprehensive survey of more than 200,000 heart attack patients in 1994/95 over the age of 65 with detailed chart review data. One example of effective Category I care is the use of β blockers for the treatment of heart attack patients. These help to block β-adrenergic receptors, thereby reducing the demands on the heart. In 1985, one study summarized the consensus knowledge: "Long-term beta blockage for perhaps a year or so following discharge after an MI is now of proven value, and for many such patients mortality reductions of about 25% can be achieved" (Yusuf et al., 1985).

At the time of the CCP survey, beta blockage, while inexpensive and off-patent, was widely variable across the country. As shown in Table 2.1, rates of β blocker use at discharge for ideal heart attack patients—that is, people for whom there was no contraindication for taking β blockers—ranged from 5 percent (McAllen, TX) and 13 percent (St. Josephs, MI) to 82 percent (Rochester, NY) and 91 percent (Dearborn, MI). The "right rate" for every region is something close to 100 percent, hence there is no need to risk adjust for differences in health.

There are two puzzling features of these patterns. The first is why overall adoption of β blockers was so low—even by 2000/2001, just two-thirds of ideal heart attack patients were being treated with beta blockers in the median state (Jencks et al., 2003). In part, it is because doctors gain little credit from doing a much better job (Phelps, 2000); patients rarely realize that they are being treated with effective care for their heart attack. But it is also a reticence to use new technologies in the absence of institutional "opinion leaders" supporting the adoption of new technologies (Bradley et al., 2005). During the 2000s, β blocker use became a standard measure of quality, reported on Medicare's "Hospital Compare" website,[18] so that by now, few hospitals report use rates below 95 percent. In general, efficient care diffuses to near-universal use, although the diffusion process may be remarkably slow (Berwick, 2003).

A more difficult puzzle is why some regions adopted so much more quickly than others; why should Rochester, NY (82 percent), and San Francisco (65 percent) be so much higher than Los Angeles (44 percent) and Chicago (36 percent)? One might understand that "opinion leaders" might differ with regard to their views of β blockers, but it is more difficult to think of why opinion leaders favoring β blockers would tend to be concentrated in Rochester, NY, rather than in Chicago. Certainly price-adjusted spending is not associated with the more rapid diffusion of β blockage ($\rho = -0.24$) (Table 2.1). Nor is per capita income, thus casting doubt on a demand-side explanation in which higher-income regions hire higher-quality physicians.[19] However, β blockage at the state level *is* associated with the adoption of other efficient technologies such as tractors in the 1920s and hybrid corn in the 1930s and 1940s, which in turn are linked by higher degrees of social capital, an index of education, civic participation, and trust (Skinner and Staiger, 2007). These correlations do not solve the puzzle of course, but do point to persistent differences across regions in the adoption of new technology, something that is also found for country-level adoption of new technologies (Comin and Hobijn, 2004).

These Category I treatments may have an outsized impact on health outcomes, but they are not likely to play a large role in explaining variations across regions in expenditures. I next turn to surgical and other preference-sensitive procedures with a greater impact on spending.

3.4. Preference-sensitive Treatments with Heterogeneous Benefits (Category II)

The first scientific study of regional variations arose in a 1938 article by J. Alison Glover on tonsillectomy rates. He calculated population-based rates for children ranging across England from 0.4 percent in Wood Green to 5.8 percent in Stoke or Peterborough (Glover, 1938). The classic study by Wennberg and Gittelsohn, using comprehensive health-level data across small communities in Vermont during the late

[18] See http://www.hospitalcompare.hhs.gov/. Since there is no longer much variation in β blocker use, some have dropped it as a marker for quality.

[19] It seems unlikely that these variations could be explained by patient demand at the individual level; it is not clear why supine heart attack patients in Rochester, NY, should know so much more about β blockers—and be insistent on demanding such treatments—than those in Chicago. One anecdotal story relayed to me was that the chief cardiologist in one hospital (in the early 2000s) responded to requests to raise β blockers by saying "Why would you ever use β blockers for someone who just had a heart attack?"

1960s, also found community-level "surgical signatures" in tonsillectomy rates, ranging from 13 to 151 per 10,000 people (Wennberg and Gittelsohn, 1973). In these small areas, a single school physician could have a disproportionate impact on surgical rates, depending on his beliefs about the efficacy of the procedure.

Why so much variation in tonsillectomy rates in the 1930s and 1960s, and why does it appear to persist into the 2000s (Suleman et al., 2010)? One reason could be a vacuum of professional guidelines on appropriateness for surgery. A 1937 textbook included a long laundry list of symptoms for which tonsillectomies were deemed appropriate, including "Any interference with respiration, day or night" (Burton, 2008). Nor had guidelines improved by the 1970s, where a qualitative study of Scottish physicians found quite different decision rules to decide who got surgery. One physician paid particular attention to inflammation near the tonsil as a "reliable" sign, while another ignored such inflammation but instead focused on cervical lymph nodes in the neck. Other physicians focused on physical diagnosis, while still others relied on medical history[20] (Bloor et al., 1978a and b).

Physicians may adopt a rule-of-thumb—recommend surgery for a certain percentage or number of recently seen patients. For example, a 1934 study by the American Child Health Association in New York was designed to measure the overall fraction of children deemed appropriate for tonsillectomy. John Wennberg described the surprising results of the study:

> The research design required random sampling of 1000 school children. Upon examination, 60% were found to have already undergone tonsillectomy. The remaining 40% were examined by the school physicians, who selected 45% in need of an operation. To make sure that no one in need of a tonsillectomy was left out, the Association arranged for the children not selected for tonsillectomy to be re-examined by another group of physicians. Perhaps to everyone's surprise, the second wave of physicians recommended that 40% of these have the operation. Still not content that unmet need had been adequately detected, the Association then arranged yet a third examination of the twice-rejected children by another group of physicians. On the third try, the physicians produced recommendations for the operation on 44% of the children. By the end of the three-examination process, only 65 children of the original 1000 had not been recommended for tonsillectomy. (Wennberg, 2008, p. 26)

This finding is supportive of a rule-of-thumb decision process, but it doesn't explain why there might be different rules of thumb across the country. Clearly, if just a few pediatricians have the responsibility for diagnosing tonsillectomy in a given region, idiosyncratic beliefs could translate into regional variations. Alternatively, a common rule of thumb could interact with exogenous factors outside the health care system. Gruber and Owings (1996) find that in areas where fertility rates fell the most, Cesarean section rates rose the most, a result consistent with one in which

[20] See Wennberg (2010) for a further discussion of these studies.

obstetricians do about the same number of Cesarean sections every year (see also Wennberg, 2010). Alternatively, one might expect to observe network effects, in which junior physicians adopt the practice style of more senior ones in the region. However, one study of Cesarean section rates in Florida found surprisingly little evidence of such spillover effects—even within practices there was a remarkably large variation in rates of Cesareans (Epstein and Nicholson, 2009).

Another key factor in affecting utilization is demand. As noted earlier in Figure 2.3, relatively small differences in demand could generate large variation in utilization, particularly where there is a vacuum of scientific evidence. Dr. R.P. Garrow, commenting upon Glover's 1938 study, noted that some of the "strange facts" regarding the unusually high rates of tonsillectomy among high-income households could be explained by "maternal anxiety" (p. 1236). Aside from the physician's disdain for such anxiety, this could either signal a pure income effect, or could also reflect a (perhaps mistaken) belief among higher income parents that tonsillectomies were the best approach to reducing discomfort for their children. Even now, most parents of children seeking tonsillectomies have "made up their mind what they want to have done beforehand" (p. 24) (Burton, 2008).

But one cannot explain the 10-fold variation across regions solely by the income elasticity of demand, time preference rates, or even possible differences in prices. Instead, the variation is likely a combination of factors: parents willing to give a "low-risk" procedure a try, coupled with a trusted family physician who is enthusiastic about the procedure, and who might not have entirely understood the risks of an adverse event; the underlying mortality rate in the 1930s was more than 0.1 percent.[21]

Back surgery is another example of Category II treatment, as discussed in section 2.3. Table 2.1 shows the variation in back surgery rates across regions in the US Medicare population. While the coefficient of variation is large (0.31), patterns of surgery are more idiosyncratic, with Bend, OR, exhibiting rates of 7.4 per thousand compared to low-rate regions such as New York (2.0) or Miami (2.4). Overall the correlation between price-adjusted spending and back surgery rates is −0.12. In other words, high rates of back surgery are slightly more likely in regions with overall lower Medicare expenditures. These rates are also higher in western states, and while one might conjecture that such residents are more likely to be engaged in outdoor activities, one might equally conjecture more back problems for industrial states with large blue-collar populations. Another example of regional variations, prescription drug spending (Medicare Part D), showed a similar lack of association with overall Medicare spending (Zhang et al., 2010a).

[21] Glover (1938) reported roughly 85 deaths per year during 1931–35, slightly more than 0.1 percent of the average of overall procedures during this period.

One explanation for these variations in Category II procedures is that some physicians and hospitals are simply better at providing specific services. For example, Chandra and Staiger estimated a Roy model of surgical treatments for heart attack patients, and found that in regions with high rates of surgical interventions, the marginal value of such interventions was considerably higher than in the low-rate areas ($g(x)$ instead of $s(x)$ in Figure 2.1) (Chandra and Staiger, 2007). They also found in regions with these high-quality surgeons or interventional cardiologists that overall survival rates were no better because of poorer-quality medical management, as reflected in the lower use of β blockers in high-surgery regions.

Similarly, Wennberg (2010) has observed that surgeons tend to specialize in a specific procedure within their field in which (presumably) they are most skilled and comfortable. This leads to a trade-off: Patients benefit from surgical specialization if they happen to be appropriate for the surgeon's favored procedure, but they could also be worse off if that procedure is not quite right for them. Physicians prescribing antipsychotics also tend to specialize in one specific treatment, particularly those with low volumes of patients or nearing retirement (Levine Taub et al., 2011).

Another example of preference-sensitive or Category II treatment is PSA testing. These simple blood tests detect early evidence of prostate cancer development in men, but there is considerable controversy about the value of such tests. First, there is a very long lag time between an elevated PSA test and the point at which prostate cancer adversely affects health. And second, many types of prostate cancer are benign—more than half of men over age 80 have evidence of prostate cancer, even when they die of something else. While there is evidence of small but significant benefits of PSA screening on survival for men under age 65 (Bill-Axelson et al., 2011), the treatments carry risks of incontinence and loss of sexual functioning. Thus preferences—quality versus quantity of life—should have an impact on decisions to be screened for prostate cancer, particularly if they vary widely across regions in the US.

More puzzling is the presence of variations for PSA testing where there really is no good evidence of benefits: for men over age 80. Studies show no benefit of either screening or treatment (versus watchful waiting) for men over age 65 (Bill-Axelson et al., 2011; Esserman et al., 2009). Indeed, the US Preventive Services Task Force recommended *against* the use of PSA screening for men over age 75 (US Preventive Services Task Force, 2008). Yet there was considerable variation across regions in 2003 rates of PSA testing for men over age 80, ranging from 2.2 percent in Burlington, VT, and 5.3 percent in Rochester, NY, to 27 percent in New York City, 30 percent in Miami, and 37 percent in Sun City, AZ[22] (Bynum et al., 2010). Rates

[22] The coefficient of variation was 0.35. The data used in the Bynum study predate the formal recommendation by the US Preventive Services Task Force; the previous guidelines had cautioned the use of PSA tests for men with life expectancies of less than 10 years. More recent unpublished data, however, suggest little downward trend.

of PSA testing for men over age 80 were positively associated with higher overall expenditure rates ($p = 0.36$).

How much of these variations are the consequence of movements along a perceived production function (because of changes in λ, as in Figure 2.1), and how much are the consequence of different production functions ($s'(x)$ versus $g'(x)$)? Like tonsillectomies, the variation is likely the consequence of both supply—physicians who follow a rule-of-thumb in checking the PSA testing box on the blood test form—but also of demand, in which 80-year-old men have grown accustomed to getting their "all clear" test results for prostate cancer while younger, and cannot imagine why they would not continue while older. (One physician explained to me that she did not have the 20 minutes to explain to these older men that they did not need the test any more.) Still, the fact that rates vary more than 10-fold between Burlington, VT, and Sun City, AZ, suggests a multiplier or network model, whether in patient demand (men want what their friends get) or physician supply (following community norms reduces the risk of a malpractice suit.)

What about geographic variation for these Category II procedures in other countries? An earlier study found evidence of variations in health care utilization in England, Wales, and Canada that on a proportional basis were similar to those observed in the US, even if the non-US countries generally experienced lower overall rates (McPherson et al., 1981). More recently, variations have been found for hip replacements in Finland (Makela et al., 2010), antibiotic prescriptions in France (Mousques et al., 2010), and the treatment of bladder cancer and antibiotic use in the Netherlands (Goossens-Laan et al., 2010; Westert et al., 2010).

Two comprehensive studies of variations in the British National Health Service (NHS) also found considerable variability in Category II treatments such as stents and hip replacements (Appleby et al., 2011; National Health Service, 2010). As the Kings Fund study showed, the extent of variation for the entire population (that is, not specific to just the over-65s) in percutaneous coronary interventions (most of which are stents) exhibited nearly 10-fold variation across regions, with a coefficient of variation equal to 0.39. That such variations are observed even in a national health system with salaried physicians suggest that it is not simply the presence of a fee-for-service Medicare system, or income-maximizing physicians in a supplier-induced demand model, that generates variations in Category II or preference-sensitive conditions.

3.5. Supply-sensitive (Category III) Treatments with Unknown or Marginal Benefits

In 1965, Martin Feldstein published a study of regional variation in hospital capacity across England, and found notable variations in beds per thousand, ranging from 4.61 in Sheffield to 6.79 in Liverpool (Feldstein, 1965). Hospital utilization is a Category III treatment because—at least for levels typically observed in developed economies—the incremental health value of greater hospital capacity is either small or zero (Fisher et al., 1994), or simply unknown.[23] These variations in hospital use did not appear to be explained by differences in health, nor did Feldstein observe the standard response to organizational scarcity, such as greater occupancy rates in regions with fewer beds, or shorter length-of-stay.

One potential explanation suggested by Feldstein for variations in hospital capacity is that building decisions were made decades ago, and hospital beds are less likely to migrate than individuals. Thus even after adjusting for disease burden, past changes in population predict current per capita bed capacity (Clayton et al., 2009). This idea was also expressed in "Roemer's law": building a hospital bed changes the informal medical rules-of-thumb for which conditions (and which severity levels) merit hospital admissions (Wennberg, 2010).

These hospital variations were also found in the Wennberg and Gittelsohn study of small Vermont communities, where rates ranged between 122 and 197 days per thousand (Wennberg and Gittelsohn, 1973). They also found a strong association between physician supply and utilization of physician services, the analogue of Feldstein's finding that hospital bed scarcity was not associated with more intensive use of each bed.

To see the variability in Category III or supply-sensitive care across the sample regions in Table 2.1, I consider two measures of end-of-life care among the chronically ill: ICU days in the last six months (2007) and physician visits in the last two years (2001—05), shown in Columns 8 and 9 of Table 2.1.[24] One might be concerned with end-of-life measures, since the treatment intensity of the region may affect the composition of the end-of-life sample: heroic efforts would save someone in a more intensive region who might otherwise be a decedent in some other region (Bach, 2010). Thus the highest cost (and successfully treated) patients would be missing from the sample of decedents in high-intensity hospitals and regions, leading to lower spending measures for higher-cost regions and conversely. Thus, estimates of end-of-life spending in theory could understate or overstate true variation, but in practice these measures are very strongly correlated with forward-looking cohorts of spending (Ong et al., 2009; Skinner et al., 2010). It is also important to note that end-of-life spending should not necessarily be interpreted as futile—physicians *ex ante* do not typically know which patients will survive—but instead as a signature of spending intensity for all chronically ill patients, some of whom die.[25]

[23] The story is quite different in emerging economies where the availability of high-quality hospital facilities is very limited.

[24] The latter end-of-life measure was limited to (and risk adjusted for) those diagnosed with serious illnesses (such as COPD, dementia, cancer, or multiple diagnoses) and who also died.

[25] An alternative approach is to use forward-looking cohorts, such as people who had heart attacks or hip fractures, although forward-looking and backward-looking measures are highly correlated (Skinner et al., 2010). In one study the correlation coefficient between the two types of measures was 0.95, although the rank ordering shifted for several of the intermediate-cost hospitals (Ong et al., 2009).

Rates of ICU days in the last six months varied widely, from 1.4 days per decedent in Grand Junction, CO, to 10.7 days in Miami; the coefficient of variation is 0.43. Similarly, physician visits ranged from an average of 38 in Grand Junction and Bend, OR, to 106 in Miami and 109 in Los Angeles.[26] These end-of-life measures are also strongly correlated with overall price-adjusted Medicare expenditures; correlation coefficients are 0.65 and 0.68, respectively (Wennberg et al., 2002).

Category III variations are also found in other countries (WIC, 2011). For example, wide variations in rates of asthma hospitalization found across regions in Canada were explained less by the frequency of emergency-room visits and more by the probability of subsequent admission to hospital (Lougheed et al., 2006). Similarly, variations for asthma hospitalizations were also variable both within and between Scandinavian countries (Kocevar et al., 2004).

One way to view these patterns of geographic variations comes from the theory of reasoned action, an approach developed by psychologists Ajzen and Fishbein (1980). In their model, individual behavior can be broken down into two parts: goals or objectives (e.g. health-seeking behavior is motivated by the desire to live more disease-free years), and beliefs about how to attain those goals. Presumably, patients and their physicians share the same broad goals: better functioning and longer lifespan. But different local health care systems may have quite different perceived approaches to attaining those goals. One study surveyed physicians across the United States and presented each with vignettes about a specific patient, and then asked the physicians how they would treat the patient (Sirovich et al., 2008). For questions where the scientific basis for treatment was clear and well established, there was very little variation in responses across regions. However, when the vignettes asked about scenarios where there was no clear right or wrong answer, there was considerably more variation across regions in how the physicians indicated they would proceed.

For example, at the UCLA hospital, where end-of-life utilization rates are among the highest in the country, the chief executive officer declared that "If you come to this hospital, we are not going to let you die." The hallmark of UCLA-style intensive care is not giving up on what might appear to be hopeless patients, with examples of both success and failure (Abelson, 2009). By contrast, end-of-life patients in low-cost Grand Junction, CO, experience a different philosophy that appears to reflect different beliefs about how to provide "best quality" care:

> Thanks to the area's single nonprofit hospice, which also offers palliative care, physicians are educated about initiating discussions with elderly patients about advance directives, and the public is informed about end-of-life choices. As a result, Grand Junction's population spends 40% fewer days in the hospital during the last 6 months of life and 74% more

[26] Physician visit measures do not include visits by medical residents, who cannot bill Medicare directly for their services. Thus true measures of physician visits are likely understated.

> days in hospice than the national averages, and 50% fewer deaths than average occur in the hospital. (Bodenheimer and West, 2010)

Perhaps it is not surprising that academic medical centers position themselves to provide more intensive care, given their relative strengths. But too little is known about the overall impact of these different approaches to treating chronic illness. While Barnato et al. (2010) found slightly higher six-month survival rates in hospitals using more intensive end-of-life care, another study at a major medical center showed worse outcomes (survival and quality of life) arising from regular care versus early palliative care for metastatic lung cancer (Temel et al., 2010).

Given the lack of strong clinical evidence favoring one approach over another, patient preferences should play a role. Some will want everything possible done for them, while others would prefer the Grand Junction model, particularly if they were being asked to pay out-of-pocket for the difference between UCLA-style care and Grand Junction-style care.[27] It seems likely, however, that regional practice norms trump patient preferences, whether in high-intensity or low-intensity regions, a result that was found in the SUPPORT study[28] (Pritchard et al., 1998).

There are several other examples of Category III treatments where the clinical value is zero or most likely even negative. For example, the use of feeding tubes for patients with advanced dementia (such as Alzheimer's disease) represents a considerable burden for confused patients but with no better longevity (Finucane et al., 1999). One study found regional end-of-life care expenditures to be strongly predictive of its use (Teno et al., 2010). Yet there was considerable variation even within regions and teaching hospitals.[29] Other examples of variation in Category III treatments include inappropriate combinations for prescription drugs, where the lack of coordination in prescriptions leads to serious health risks (Zhang et al., 2010b), and the use of two CT scans on the same day, exposing patients to extra radiation with no clinical benefit (Bogdanich and McGinty, 2011).

Why do regions differ so much with regard to these Category III treatment rates? As noted above, Atul Gawande documented higher spending rates in McAllen, TX (as shown in Table 2.1), with the most pronounced entrepreneurial efforts focused on home health care, where physicians would often form a business affiliation with a home care agency (Gawande, 2009). As a consequence, price-adjusted spending for home health services per

[27] More complicated still is when family members also have strong preferences regarding treatment options.

[28] Another set of studies examined patient preferences for health care (e.g. if your doctor said you probably do not need an X-ray, would you still want one?) at the individual level for Medicare enrollees. While there was considerable variation in preferences across individuals, there was little difference in the fraction of patients wanting more care across regions—in other words, preferences did not appear to explain differences across regions in utilization (Anthony, et al., 2009; Barnato, et al., 2007).

[29] Cedar-Sinai and UCLA hospitals in Los Angeles are both very high-cost hospitals, as measured by end-of-life treatments, yet the use of feeding tubes for advanced dementia patients was zero at UCLA, in contrast to Cedar-Sinai, whose rate was more than double the national average (Teno et al., 2010).

Medicare enrollee was $3,496 in the McAllen HRR, or about seven times the national average of $496 and 13 times per enrollee spending in Grand Junction.

Why McAllen? In 1992, McAllen and El Paso were nearly identical with regard to Medicare spending, but by the 2000s they had sharply diverged. One anecdotal story from a physician recruiter suggested that it was far more difficult to recruit physicians to work in McAllen than in El Paso, requiring larger bonus payments to attract physicians there. The selection process would therefore lead to a population of physicians who were unusually motivated to respond to incentives. In sum, high-cost regions may be high for at least two reasons. The first is a larger perceived or actual productivity of health care ($g'(x)$ versus $s'(x)$ in Figure 2.1). The second is an entrepreneurial environment (one that could even verge on fraud) leading to a low or even negative λ (as in Figure 2.1).[30] The former explanation can hold under any health care system, fee-for-service or not. The latter model is better suited for explaining "outlier" spending measures in fee-for-service-based insurance programs for regions such as Miami and McAllen.

4. ESTIMATING THE CONSEQUENCES OF REGIONAL VARIATION: GEOGRAPHY AS AN INSTRUMENT

To this point, I have focused solely on whether geographic variations in utilization and expenditures exist, and if so what are the causes of such variations. This section considers the consequences of greater health care intensity, a topic on which there is a growing literature, with often seemingly contradictory results—sometimes positive coefficients, sometimes negative, other times zero.

To make sense of the often disparate results, consider a stylized model of aggregate health care outcomes, where the aggregation is across individuals in a specific region.[31] These individuals may have a given disease (like a heart attack), or the study may aggregate across all diseases. Let survival or functioning (or both—in the sense of quality-adjusted or disability-adjusted life years) be written S_j for region j, where

$$S_j = X_j\beta + m_{1j}\gamma_1 + m_{2j}\gamma_2 + m_{2j}\gamma_2 + \varepsilon_j \tag{2.5}$$

The variables m_i are the dollar-equivalent input quantities for each of the three treatment categories discussed in section 2 above, while the vector X measures health-related

[30] Miami appears to be a "hot spot" for fraud, as evidenced by one newspaper story about Dr. Christopher Wayne, the "Rock Doc," who billed Medicare $1.2 million in 2008, mostly for physical therapy (Schoofs and Tamman, 2010). But fraud alone is unlikely to explain why Miami is such an outlier, since such behavior is also pervasive in New York, Los Angeles, and Detroit (Schoofs et al., 2011).

[31] I ignore here the considerable challenge of determining the "correct" spatial unit of analysis (Fotheringham and Wong, 1991).

risk adjusters, β the vector of coefficients, and ε is the error term. The key coefficients are γ_i , or the average marginal productivity of input i, with an assumed ranking of $\gamma_1 > \gamma_2 > \gamma_3$ reflecting the assumption above that, on average, Category I inputs are more cost effective than Category II, and Category II more cost effective than Category III.

Aggregate per-enrollee expenditures $M_j^\star$ are given by

$$M_j^* = P_j[m_{1j} + m_{2j} + m_{3j}] \tag{2.6}$$

where the aggregate price P_j reflects the differential price indices for reimbursements across regions. Thus, price-adjusted spending m_j is defined implicitly by

$$m_j = m_{1j} + m_{2j} + m_{3j} \tag{2.7}$$

Now that a set of outcome and spending variables has been defined, one can turn next to the variety of studies seeking to ask the question of "Is more better?" There are two general categories of such studies: The first considers specific inputs and thus can be viewed as capturing an estimate of a specific γ_i. Another set of papers considers a broader classification of aggregate spending, and in some cases uses an estimate of one type of spending, such as m_3, as an instrument for other inputs in the production function.

As an example of the first type of study, Glover's original 1938 paper considered a natural experiment in which Hornsey Borough declined suddenly from 186 tonsillectomies per 1,000 in 1928 to just 12 in 1929, and remained low thereafter owing to the "courageous" efforts of the local doctor. The outcome measure, otitis media (an inflammation of the inner ear), continued a secular decline during this period, and so Glover therefore concluded that the fall in tonsillectomy rates carried no risks to children (Glover, 1938). The estimated marginal impact of tonsillectomies on otitis media (γ_2) was therefore zero.

Amber Barnato and colleagues in turn estimated the association between greater intensity of care (higher utilization) and 30-day and six-month survival in Pennsylvania hospitals (Barnato et al., 2010). Because so little is known about the incremental effectiveness of the intensity of hospital treatments, this study corresponds to an estimate of γ_3 for Category III treatments.[32] The key feature of this study is that they were able to measure specific components of treatment: ICU use, mechanical ventilation, hemodialysis, tracheostomy and feeding tubes. On average, they found survival benefits of more intensive care: a roughly $14,000 increase in per capita expenditures for these treatments translated into a 1.5 percent improvement in the chance of surviving an extra six months, with unclear evidence of persistence beyond six months. The largest benefits were seen at the lowest level of spending, where the

[32] See Fisher and Skinner (2010) for further discussion of this and other studies.

hospitals may have lacked a fully staffed ICU facility. For this case, γ_3 was estimated to be positive, albeit with poor cost effectiveness.[33]

Another example of using geography to estimate specific treatment effectiveness comes from the classic study by McClellan et al., who used differential distance to a catheterization laboratory to study the effectiveness of surgical interventions for heart attack patients (McClellan et al., 1994). Their results suggest modest cost-effectiveness of surgical interventions; a different study showed such beneficial results persisting over long periods of time (Cutler, 2007). One potential limitation of these studies, recognized by the authors, is that hospitals with catheterization laboratories may also provide higher quality care along other dimensions—that is, the observable Category II measure could be correlated positively (or negatively) with other dimensions of care.[34]

One study compared state-level Medicare expenditures with state-level process quality measures like beta blocker use after heart attacks, or flu shots (Baicker and Chandra, 2004). They found a negative association between overall expenditures and effective (or Category I) care for the Medicare population.[35] The advantage of this study is its simplicity; process measures of care did not require risk adjustment since heart attack patients in Louisiana should be as likely to receive β blockers at discharge as those in New Hampshire, especially if they are sicker. This study has sometimes been interpreted as showing that "more is not better," but it tells us little about the marginal effectiveness of specific treatments (γ). Instead, it tells us about the partial correlation coefficient $r_{1M^\star}$ between unadjusted spending $M^\star$ (as in equation (2.6)) and effective care m_1. Thus effective or Category I care is not necessarily positively associated with higher levels of Category II or III care. (This can also be seen in Table 2.1 by the negative association between spending and β blocker use.) Another paper used more recent quality data from Medicare's Hospital Compare program at the hospital level to find negative or zero correlations between reported quality and end-of-life spending (Yasaitis et al., 2009).

Other studies have used end-of-life and other types of measures as an instrument for overall expenditures. For example, a two-part study in the *Annals of Internal Medicine* examined patients who were hospitalized with one of three different conditions: heart attack, hip fracture, and colon cancer (Fisher et al., 2003a and b). First, they divided regions into five equally sized quintiles based on average end-of-life spending in the region. In other words, the "look-back" end-of-life measures were

[33] Another approach is to consider supply measures of specific inputs such as specialists; one study found positive but rapidly diminishing returns (in terms of infant mortality) to an increased supply of neonatologists (Goodman et al., 2002).

[34] Also see Xian et al., who find beneficial effects of stroke centers on health outcomes of stroke patients (Xian et al., 2011).

[35] This correlation is specific to Medicare quality measures and Medicare expenditures, but may not extend to non-Medicare data (Cooper, 2009).

used to assign regions to quintiles; Los Angeles was a high-cost region (for end-of-life care) and so anyone with a heart attack, hip fracture, or colon cancer in Los Angeles was assigned to that quintile.

They then "looked forward" to see what happened to each of the three risk-adjusted cohorts of patients, starting on the day the patient was hospitalized for heart attack, hip fracture, or colon surgery.[36] Patients treated in regions where utilization (and spending) were higher received about 60 percent more care over the first year after their initial hospitalization. But in general, there was no pattern showing better risk-adjusted outcomes when compared with those treated in regions where utilization was lower—of the 42 separate hypothesis tests in the paper, 23 showed significantly worse outcomes in high-spending regions, 14 showed no significant effects, and five showed significant positive effects.[37]

In the context of the model above, the expected value of the reduced-form coefficient arising from this type of regression, where a Category III measure is used as an instrument, is given by the following:

$$E\{\hat{\gamma}\} = \gamma_3 + r_{13}\gamma_1 + r_{23}\gamma_2 \tag{2.8}$$

That is, without including the other categories of treatment on the right-hand side, the estimated coefficient implicitly captures the primary estimate γ_3, but also the estimates of average marginal effects for Category I and II treatments, multiplied by the partial regression coefficient of these different components on m_3. For example, suppose that γ_1 is large and positive (by assumption), but that Category I effective treatments are negatively correlated with Category III supply-sensitive care for these specific cohorts. Even if γ_3 is positive, when $r_{13} < 0$, the estimated *association* between m_3 and risk-adjusted outcomes could be negative or zero. Or conversely, if the coefficient γ_3 is zero or even negative, a positive association between Category III spending and effective Category I care—as has been found in cancer treatments (Landrum et al., 2008)—could still yield a positive estimated coefficient when end-of-life spending is used as an instrument. In other words, it is not whether "more spending is better" but instead how the money is spent—is it for home health care yielding no health benefits at the margin (McKnight, 2006), or primary angioplasty for heart attack patients?

A number of other studies have since been published with end-of-life measures using either the reduced form approach in the Fisher et al. studies, or an explicit instrumental variables approach (Skinner et al., 2005). As noted above, the use of end-of-life care as an instrument could bias against finding that more spending is

[36] They also considered data from the Medicare Current Beneficiary Survey and the Cooperative Cardiovascular Project, which included chart data and thus provided the highest quality risk adjustment.

[37] Adjusting for spatial clustering (which was not done in these studies) most likely would have moved several of the negative and positive results into the insignificant bin.

associated with better outcomes—as this is the component of spending *least* likely to yield health benefits—but a more recent set of studies has found positive associations between end-of-life spending and health outcomes. These have differed from the earlier studies by including different disease categories, using two years of "start-up" data to collect comorbidities (and where respondents must remain alive to be included in the cohort), or by focusing on in-hospital mortality for all age groups (Hadley et al., 2011; Ong et al., 2009; Romley et al., 2011; Silber et al., 2010).

Still others have attempted to develop a natural experiment by focusing on tourists who got sick and were admitted to hospital in Florida (Doyle, 2010). In this case, greater intensity of care for acutely ill tourists was found to yield real benefits. For non-tourists, however, more intensive care was not associated with better outcomes; this is either consistent with heterogeneity in benefits (tourists benefit most from intensive care) or a positive correlation between high spending areas and unobservable poor health of residents.[38] More generally, the wide range of estimates could be explained by heterogeneity across diseases and treatment strategies in the correlations r_{ij}.

One way to address this problem is to enter inputs for Category I, II, or III treatments directly, and thereby attempt to estimate separate γ coefficients rather than some weighted average of the underlying coefficients. One study using hospital-level data found a faintly negative association between overall risk-adjusted and price-adjusted spending and risk-adjusted one-year survival for heart attack patients in the Medicare program. This can be explained in party by a slightly negative association between Category I and total spending measures (Skinner and Staiger, 2009). However, when hospital-specific Category I treatments were included in the regression (aspirin, β blocker, and primary reperfusion such as angioplasty or clot-busting drugs), along with total expenditures ($m_2 + m_3$) on the right-hand side of the equation, both coefficients became positive—with γ_1, the effect of Category I treatments, dominating the (positive, but diminishing) impact of spending.

Figure 2.5 captures their results graphically; the empty dots represent hospitals with rapid adoption of Category I treatments, while the full dots are those with slow adoption. The functions $s(x)$ and $f(x)$ measure the conventional "production function" association between spending more and outcomes. Thus knowing the simple correlation between spending and survival in Figure 2.5, which as drawn could be either positive or negative, tells us little about the deeper parameters of the model.[39]

Other studies have found similar patterns, including one comprehensive study of mortality rates for Medicare beneficiaries undergoing major vascular, orthopedic, and

[38] Other more recent studies found negative or zero associations between spending, whether in levels (Glance et al., 2004), or in growth rates (Rothberg et al., 2010a).

[39] Another approach is to consider Category I and III treatments in the context of a difference-in-difference model, as in Skinner et al. (2006).

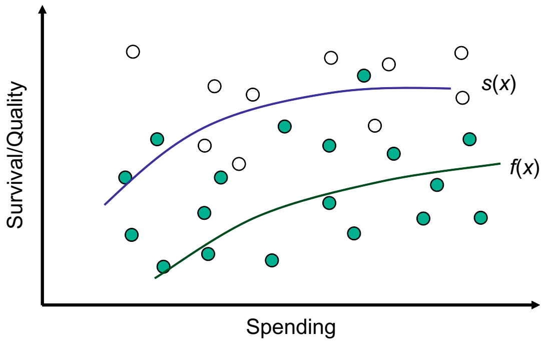


Figure 2.5 Hypothetical spending and outcome measures.

general surgical procedures at US acute care hospitals (Silber et al., 2010). The primary results were that when end-of-life hospital resource use in the region is higher, 30-day surgical mortality rates and the relative risk of failure to rescue (having a complication and dying) were lower. In other words, hospitals spending more on Category III treatments also experienced better Category II outcomes for their surgical patients.

These results are also consistent with the pattern pictured in Figure 2.5, in finding that a $10,000 increase in end-of-life expenditures, while substantially improving survival in the first 30 or 90 days, is more modest in the longer term, leading to just a 0.12 percent increase in the probability of surviving one year post-surgery (Fisher and Skinner, 2010). And like Figure 2.5, the individual-specific variations in hospital productivity are very large in magnitude relative to the treatment effects or slope of the production function.[40]

These findings are also consistent with other evidence on productivity. For example, the finding that total factor productivity differences explain much of the variation in GDP per capita across countries is by now well established, as is the finding that some countries (like some health care systems) are consistently ahead in innovation (Comin and Hobijn, 2004). Similarly, the lack of correlation between the level of regional health care spending and growth in such spending (Chernew et al., 2010a) is also consistent with the macroeconomics literature on the weak convergence properties of country-level per capita GDP. As noted above, productivity differences across hospitals are consistent with similar variation across firms in the concrete industry

[40] Focusing on the 30-day mortality rates, the standard deviation for the "across hospital variation" was 0.19396, while the (linear) coefficient on end-of-life spending was 0.06584 (in units of 10,000 dollars). Thus increasing end-of-life spending by $10,000 was roughly equivalent to a 1/3 standard deviation increase in the random effect parameter (or a movement from the 50th to the 63rd percentile). See also Kaestner and Silber (2010) for additional evidence on 30-day outcomes across a variety of conditions. I am grateful to the authors for sharing these estimates from their model.

(Syverson, 2004). The lesson of the concrete industry, however, is important: we do not necessarily think that creating a government-financed Concrete Innovation Center (CIC) would necessarily improve productivity in that sector. What then are the policy levers in health care that might improve efficiency by addressing regional variations in health care?

5. INEFFICIENCY AND THE POLICY IMPLICATIONS OF REGIONAL VARIATIONS

There are a variety of approaches to estimating the overall degree of inefficiency in the US health care system. One approach that focuses on benchmarking low-cost communities yields estimates of efficiency costs of 15—25 percent, with 30 percent an upper limit; these assume that the benchmark regions are perfectly efficient, which is overly optimistic—Bend, OR, is a low-cost region despite its high rates of back surgery.[41] A McKinsey Report estimates that the US wastes $650 billion (or 30 percent of total spending on health) relative to health care systems in other developed countries (McKinsey, 2008), while Thomson Reuters estimates 33 percent waste (Kelly, 2009). However, these estimates ignore the potential loss in health outcomes arising from the underuse of efficient treatment—the vertical variation in Figure 2.5, not just the horizontal variation. Accounting for such differences would lead to substantially higher levels of inefficiency relative to overall expenditures.

But how much of that 20 or 30 percent waste is really extractable through public policies? For some treatments where procedure rates are either too low or too high, simply publishing and circulating region- or hospital-specific measures can help to reduce inefficiency. Following the dissemination of area tonsillectomy rates from Wennberg and Gittelsohn's 1973 study, rates dropped from 60 to 10 percent in Morrisville, VT, one previously high-utilization community (Wennberg, 2010). The adoption of β blocker use as a publicly reported quality measure has increased its diffusion to near-universal use among appropriate patients. In general, the reporting of quality measures has been found to affect patient demand, but public reporting can lead to perverse outcomes if providers "game" the measures (Dranove, 2011). For example, one study found higher rates of cardiac bypass surgery as surgeons sought healthier patients to improve their quality measures (Dranove et al., 2003). Public reporting of Category III treatments might also affect patient demand if there were clear risks associated with high rates, for example receiving two CT scans on the same day (Bogdanich and McGinty, 2011). But given the very low cost-sharing in most

[41] For example, see Fisher et al. (2003a and b), Skinner et al. (2005), Sutherland et al. (2009).

health care systems, fewer patients would be scared away from hospitals simply because of their very high rates of overall spending.

Another approach to reducing unwarranted variation for preference-sensitive treatments is the use of decision aids for patients to make informed choices. These typically involve DVDs that present both probabilities and magnitudes of benefit and side-effects, as well as patient interviews describing why they did or did not choose the treatment. Whether utilization rates rise or fall (and typically they fall), this approach leads to greater efficiency with regard to matching patient preferences to treatment strategies (Barry, 2002; O'Connor, et al., 2004). As well, making decision aids the standard for informed choice has potential to reduce the likelihood of malpractice cases (King and Moulton, 2006).

None of these proposed reforms are likely to have much impact on regional differences in big-ticket Category III expenditures. One approach to addressing such variation is simply to reduce reimbursement rates in high (health-adjusted) spending areas. Certainly there is evidence that current adjustments for prices do not always reflect actual costs of doing business (IOM, 2011). But adjusting prices is a very blunt instrument, does less to improve productivity, and could in fact lead to worse outcomes (Dranove, 2011). One largely unexplored approach is to use quantity regulation to reduce regional variation, for example by buying back older MRIs in regions with high rates of imaging, or stricter enforcement of "Certificate of Need" programs.

The 2010 health care reform legislation in the United States hoped to capture some cost savings from regional variations by implementing nationwide "accountable care organizations" (ACOs) that can in theory hold down cost growth while maintaining or improving quality. The ACO was designed to reduce costs by instituting a system of shared saving in which holding growth rates below a benchmark yields bonus payments from Medicare, but exceeding a different benchmark triggers penalties.[42] The theory behind these reforms is that the physician—hospital network (as in section 3.1 above) is the appropriate decision-making unit; the providers know better than regulators what types of Category III expenditures can be cut or how care can be reorganized to maintain quality but reduce cost. But should ACOs be expected to reduce regional variations in expenditures?

In theory, ACOs could generate the greatest savings in the highest-cost regions, which should attenuate regional variations. As well, built into the legislation is an updating rule that further encourages convergence, since percentage growth rate benchmarks are defined relative to the national average, and not to the region. Thus an update of 4 percent of the national average would be translated to a dollar amount applied consistently to all regions, leading to a much smaller proportional update in Miami compared to Grand Junction.

[42] New ACOs can avoid penalties for the first few years.

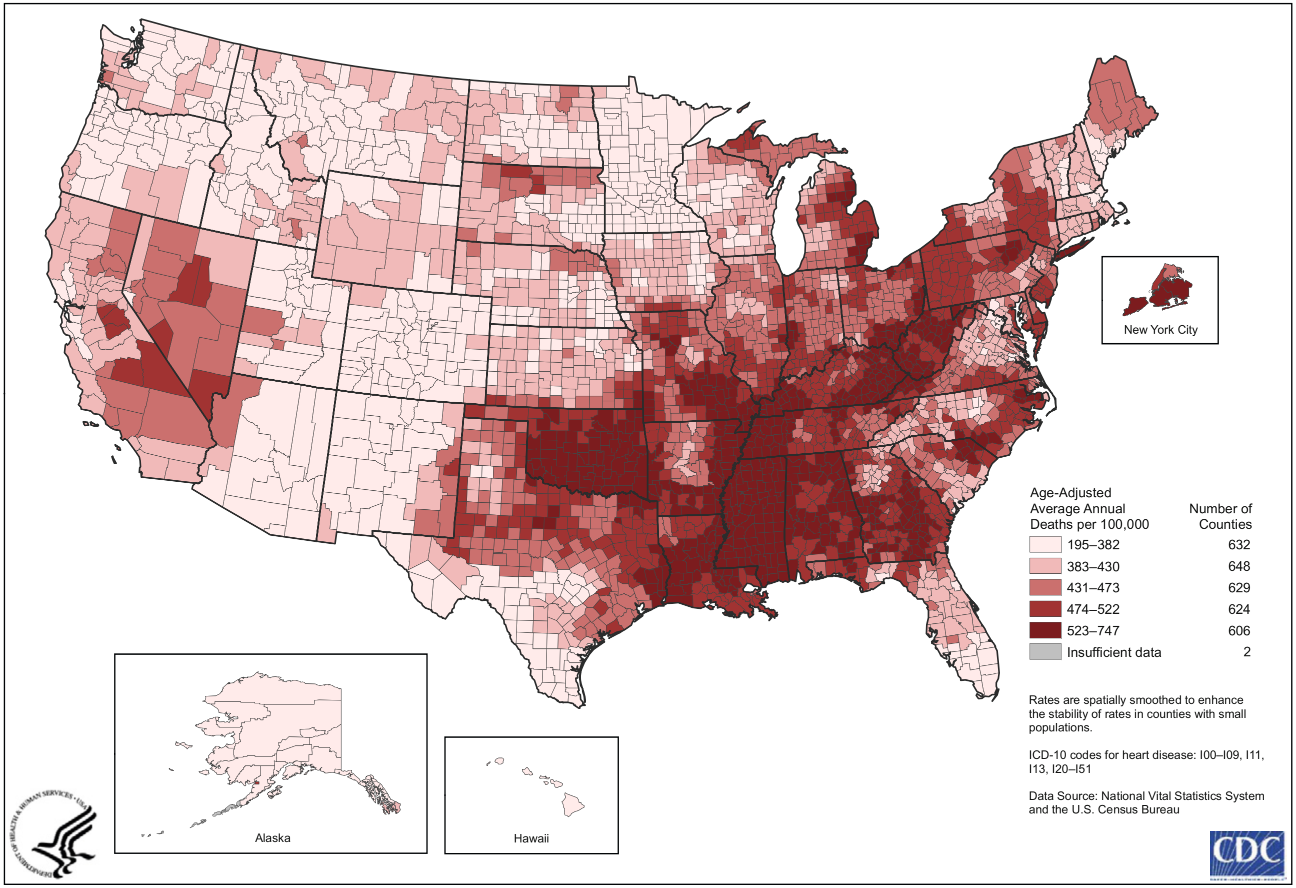
A different approach to health care reform comes from "premium support" plans in which enrollees receive a voucher with a preset amount, used as credit towards the purchase of a private insurance policy. Most notably, such an approach was proposed by Representative Paul Ryan in 2011, but a variety of other voucher plans, albeit with more generous premium support and greater regulatory control, have been proposed in the past (Emanuel and Fuchs, 2005).

Voucher plans could represent a very direct way to attenuate regional variations in spending. They would most likely provide different dollar amounts depending on health status, but the key unknown is to what extent they would accommodate existing regional variation not caused by health differences. Would Congress really allow residents of Miami to receive vouchers worth twice as much as those in Grand Junction? Conversely, if vouchers adjust only for individual health status and price differences, how would the consequent precipitous decline in the regional variation in federal Medicare expenditures affect the organization (and quality) of care in Miami (Brownlee and Schultz, 2011)?

As noted in section 3.1, risk adjustment for populations with different health status is particularly challenging whether in ACOs or for risk-adjusted vouchers. Tying the payment level (and performance or outcome measures) to the average level of illness among plan enrollees will create financial incentives for "gaming" the system, whether by diagnosing more disease or by avoiding the higher cost patient's conditional on their risk-adjustment score (Brown et al., 2011b). In sum, it is too early to tell how successfully new policies will pare away at regional variation, but improved risk adjustment and better ways of measuring health system performance and quality are all necessary (if not sufficient) steps.

6. REGIONAL VARIATIONS IN HEALTH OUTCOMES

One limitation of this study has been the emphasis on regional variations in health care utilization rather than regional variations in health. It is important to note that there are also clear geographic patterns in health. One study documented variations in life expectancy across counties in the United States that varied by as much as 15 years, for example (Kulkarni et al., 2011). And Figure 2.6 shows death rates from heart disease for people over age 35, based on Centers for Disease Control (CDC) data, by US county. The magnitude of regional variation in heart disease is larger than for many health care services, ranging from less than two deaths to over seven deaths per 1,000, with strong patterns of spatial correlation particularly in the South. Nor do these rates appear to be highly correlated spatially with actual Medicare expenditures (Figure 2.4). While there is a growing literature devoted to measuring and



Rates are spatially smoothed to enhance the stability of rates in counties with small populations.

ICD-10 codes for heart disease: I00–I09, I11, I13, I20–I51

Data Source: National Vital Statistics System and the U.S. Census Bureau

Figure 2.6 Heart disease death rates 2000–2006, adults age 35+, by county. *Source: http://www.cdc.gov/dhdsp/maps/national_maps/hd_all.htm*

understanding the geography of health and health care (Cromley and McLafferty, 2002), we do not know as much about how geographical patterns of health care expenditures and quality affect geographical patterns of health outcomes. For example, how much do the low process quality measures in Louisiana and Mississippi contribute to the higher disease burden and mortality in those states?

It is reasonable to view regional variations in meat and poultry consumption, attendance at yoga and spinning classes, or smoking and drinking, rather than regional variation in health care utilization, as the important causal factors explaining regional variation in health. This was a point made early on by Victor Fuchs; despite similar levels of health care spending in Utah and Nevada, there is much less disease in Utah (Figure 2.6), most likely the consequence of a higher fraction of Mormons in Utah who eschew smoking and drinking (Fuchs, 1998).

It is less clear how efforts to improve health by changing lifestyles and behavior should account for geographical variation. If the government chooses to tax soda, for example (Brownell et al., 2009), should rates of taxation or enforcement depend on one's state of residence? As well, taxes on poor health habits are typically borne by the individuals, and not financed through massive transfer programs such as Medicare and Medicaid, so both the efficiency and equity issues are not so closely tied into one's zip code of residence. Still, the remarkable geographic patterns of poor health are highly suggestive of network factors not yet entirely well understood (Christakis and Fowler, 2007).

7. DISCUSSION AND CONCLUSION

The regional variations literature reviewed typically appears in the health services research literature and is not always visible to the practicing health economist. Not that there's anything wrong with that, but the insights of this literature can often be used to shed light on the efficiency of health care markets, as well as providing new approaches to causality and risk adjustment. Taken as a whole, the literature points to a number of factors leading to "warranted" variation in health care expenditures, but there remains persistent and sometimes large differences in both rates of utilization and quality of care that are not explained by prices, illness, or income, or other factors. Nor are aggregate utilization rates systematically associated with health outcomes; it appears to depend more on how the money is spent than on the total amount spent.

But there is also much that is not well understood about regional variations. Most of the evidence thus far identifies regional variation as a residual, and not something that can be predicted beforehand, for example being able to foresee in 1992 that

McAllen would have grown so much more rapidly than El Paso. One can speculate that the level and growth of spending is a function of entrepreneurial capacity, market competition, the relative generosity of private firms and insurance companies, and patient preferences, but at this point we do not yet have a unified theory of regional variation that would allow us to *predict* the future evolution of health care costs and quality diffusion.

I return to the original question of why should variations in health care be viewed any differently from variations in the consumption of meat and poultry? There are two key differences. The first is that the geographic variations are being financed largely by third parties, and so the costs of regional variations in Category III treatments are borne not by the patients receiving such treatments, but by workers experiencing stagnating wages owing to health insurance premium hikes, or taxpayers facing higher statutory rates (and tax distortions) to maintain growth in Medicare spending (Baicker and Skinner, 2011). By contrast, most of the cost arising from overconsumption of marbled beef is borne by the individual (and her family) through a reduction in life expectancy. And second, existing regional variations in health care utilization are symptomatic of an enormous lack of knowledge about what works and what does not in health care—something that is less of a concern for poultry consumption.

This chapter has also highlighted some of the key difficulties in better understanding the interplay between and among supply and demand in health care markets. There are complex networks of primary care physicians who refer to specialists, who in turn recommend procedures to patients who have often done their research on the internet, leading to challenges in allocating how much of the regional the variation arises from patient demand, physician beliefs, financial incentives, or capacity constraints (Bederman et al., 2011). While unraveling this complex structure presents modeling and empirical challenges, the remarkable differences in regional practice styles and outcomes provides a fertile ground to identify, measure, and one hopes reduce the vast degree of inefficiency in health care worldwide.

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