

Productivity Dispersion in Medicine and Manufacturing[†]

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A central observation about the US health-care sector is the existence of substantial differences in productivity across regions and across hospitals. Annual Medicare spending per capita ranges from \$6,200 to \$16,300 across geographic areas, yet health outcomes do not positively covary with these spending differentials; similar patterns have been documented across hospitals within geographic markets (Skinner 2011). This has generated voluminous academic research trying to understand the root causes of productivity dispersion and what can increase productivity at underperforming hospitals (e.g., Skinner and Staiger 2009; Finkelstein, Gentzkow, and Williams 2014). These *Dartmouth Atlas* facts have also attracted considerable popular attention (e.g., Gawande 2009), and were heavily cited during the discussions around the Affordable Care Act (e.g., Office of Management and Budget 2009).¹

Both academic and policy discussions of productivity dispersion in healthcare typically ignore the well-documented existence of

enormous productivity dispersion within manufacturing industries as well. For example, on average within US manufacturing industries, the ninetieth productivity percentile plant creates almost twice as much output as the tenth percentile plant, given the same inputs; this dispersion likewise exists within and across geographic markets (Syverson 2011).

We estimate the extent of productivity dispersion across US hospitals in treating heart attacks² and compare it to productivity dispersion within US manufacturing industries. Measuring productivity is notoriously difficult, and cross-industry comparisons are notoriously difficult to interpret. These important caveats notwithstanding, our basic finding is striking and, we believe, surprising.

We estimate that productivity dispersion across hospitals in treating heart attacks is quantitatively similar to or slightly smaller than productivity dispersion within narrowly-defined manufacturing industries. Figure 1 provides one illustrative example (we discuss more comparisons below), looking at productivity dispersion in ready-mixed concrete, which, like healthcare, is produced and consumed locally; Figure 1 shows slightly lower productivity dispersion in heart attack treatment across hospitals than across ready-mixed concrete plants.

I. Empirical Approach

A. Setting, Data, and Estimation

We estimate hospital productivity (TFP) in the treatment of heart attacks (also known as acute myocardial infarctions or AMI). We focus on heart attacks for several reasons, including their importance as a cause of death and the broad agreement that survival—which we can measure well—is the key output.

²We provided substantially more detail on estimation and results in our earlier working paper (Chandra et al. 2013).

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¹These can be found at <http://www.dartmouthatlas.org>.

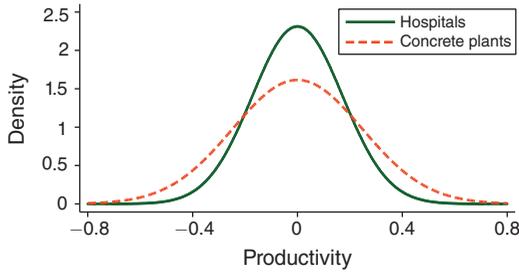


FIGURE 1. PRODUCTIVITY DISTRIBUTION ACROSS HOSPITALS AND ACROSS MANUFACTURERS

Note: Figure shows the fitted normal density approximation of the national, within-year productivity distribution for hospitals treating AMI patients and for concrete plants.

We posit a patient-level log health production function:

$$(1) \ln(y_p) = \ln(A_{h,t}) + \mu \sum_k \alpha_k \ln(R_{p,k}) + \mu \ln(x_p) + \varepsilon_p,$$

where output (y_p) is survival of patient p treated at hospital h in year t , x_p is a measure of hospital inputs used to treat this patient, and $R_{p,k}$ is a vector of k observable, patient-level factors (“risk adjusters”). The parameter μ is the elasticity of survival days with respect to risk-adjusted inputs. Our key focus is on $\ln(A_{h,t})$, which measures total factor productivity (TFP) of hospital h in year t ; empirically, our TFP estimates are the coefficients on a set of hospital-year fixed effects.

Our data are a census of Medicare Part A (i.e., inpatient hospital) claims for AMI Medicare patients from 1993–2007. We exclude patients who have had an admission for an AMI in the prior year and hospital-years with fewer than five AMI patients. Our data consist of about 3.5 million AMI patients, ages 66 and over, in 55,540 hospital-years and 5,346 unique hospitals.

B. Estimation Challenges

In any setting, estimating productivity is conceptually straightforward but practically challenging (Syverson 2011). Hospital productivity is no exception; it avoids some well-known issues (for example we can measure output directly rather than relying on revenue proxies for output) but also generates new ones (such as

potential heterogeneity across hospitals in their patients’ baseline survival rates).

Our baseline output measure (y_p) is the number of days that the patient survives after receiving initial treatment, up through the first year; it is bounded from below at 1 and above at 367 days. About two-thirds of our sample survives past one year; average survival days through one year, censoring anyone who survives more than one year at 367 days of survival, is 268 days (standard deviation = 149). Our findings are robust to measuring survival over shorter (e.g., 30 days) or longer (e.g., five year) windows.

Input measurement poses a key challenge for productivity estimation. We experimented with a variety of approaches—none of which is perfect—and are reassured that our productivity dispersion findings are robust across them. Our baseline input measure is a single input index of the (dollar-converted) sum of diagnostic-related group (or DRG) weights during the first 30 days following a heart attack. DRG weights reflect the Centers for Medicare and Medicaid Services’ (CMS) assessment of the resources necessary to treat a patient in a given DRG. On average, about \$16,000 worth of hospital inputs are used in the treatment of patients in this study in the 30 days following a heart attack, with a standard deviation of about \$12,000. Our results are similar if we instead measure inputs over the first seven days or first year following the heart attack.

Our input measure, while standard in the literature, carries the caveat that it does not reflect actual inputs used but rather CMS-defined expected inputs based on the patient’s diagnosis and broadly defined treatment approach. Alternatively, we measured inputs by the specific, detailed procedures performed and length of stay in the hospital in a multi-input production function; we also explored including non-hospital inputs for the patient (e.g., outpatient services), or defining inputs based on Medicare spending on the patient. Our findings are generally robust to the input measurement approach.

In a typical setting, productivity is the residual in a firm-level regression of outputs on inputs; therefore, estimates of the scale parameter μ in equation (1) may be biased by a correlation between input choice and the residual (productivity). In our setting, however, because we observe production at the unit (patient) level,

we can include hospital-year fixed effects, estimating μ solely from within-hospital-year variation. However, our estimate of μ will be biased if, within hospital-year, hospitals choose different observable input levels for patients who differ unobservably in their latent survival, or if their choice of unobservable inputs is correlated with observed inputs. We are therefore reassured that our results are similar if we impose, rather than estimate, various values for μ , in an index-number, or Solow residual, approach to measuring productivity.

Because patients are inherently heterogeneous, survival may depend on patient characteristics, which may be correlated with input choices; the marginal effect of inputs on survival may also vary with patient characteristics. To capture both of these effects, we follow the standard approach in the literature and include controls for patient health ($R_{p,k}$). Our baseline specification includes a full set of interactions between age, gender, and race, as well as indicator variables for whether the patient has been admitted to the hospital in the previous year with any of 17 different co-morbidities. Our main results are not sensitive to using fewer or more (for a subsample of patients where they are available) risk adjusters.

Finally, we apply the standard empirical Bayes shrinkage techniques to address potential over-dispersion of our TFP estimates.

II. Results

As a “reality check” on our TFP estimates (the hospital-year fixed effects from equation (1)), we verified that they correlate positively in the cross-section with observable and independently gathered hospital quality measures, such as publicly-reported CMS measures of the hospital’s conformance with established clinical guidelines for AMI care like administering beta blockers and the Bloom et al. (2012) measure of hospital management quality.³

We estimate an average within-year standard deviation of national hospital productivity for AMI treatment of 0.17; the 90–10 range is 0.44 and the interquartile range is 0.23. In other words, an AMI patient treated at a ninetieth per-

centile productivity hospital is expected to survive more than 1.55 times ($e^{0.44} = 1.55$) longer than had the patient been treated in the same manner at a tenth percentile hospital.

Figure 1 shows productivity dispersion for ready-mixed concrete (standard deviation = 0.25).⁴ Like healthcare, concrete is consumed and produced locally, so that spatial differentiation (i.e., physical distance) can be an important barrier to competition; however, concrete is less differentiated than AMI treatment, insurance does not dampen price sensitivity, consumers are likely well informed about their choices, and prices aren’t set administratively.

Estimates of productivity dispersion in other US manufacturing industries also tend to be slightly larger than our estimates for healthcare. Looking across a large number of narrowly-defined US manufacturing industries, researchers have estimated an average within-industry standard deviation of productivity of 0.22 (Foster, Haltiwanger, and Syverson 2008) and 0.39 (Bartelsman, Haltiwanger, and Scarpetta 2013), and an interquartile range of 0.29 (Syverson 2004a). As we describe in more detail in Chandra et al. (2013), the more limited work on productivity dispersion in service industries finds dispersion that is roughly similar to manufacturing.

III. Discussion

At a broad level, our results seem at odds with the conventional wisdom that variation in healthcare productivity is due to idiosyncratic features of the healthcare sector, such as the lack of consumer information on hospital quality, the lack of price sensitivity by generously insured consumers, and the absence of market-set prices in favor of public sector reimbursement. More speculatively, they suggest that the healthcare sector may not be greatly more insulated against demand-side competitive pressures than other sectors, as productivity dispersion has been shown, both theoretically and empirically, to shrink with greater competition within and across industries (e.g., Syverson 2004a, b).

⁴We estimate productivity dispersion in concrete using data from 1972–1997 from the Census of Manufactures; our estimation approach (details of which are provided in Chandra et al. 2013) closely follows that in Foster, Haltiwanger, and Syverson (2008).

³We are extremely grateful to Nick Bloom for providing us with these measures.

Naturally, however, there are real concerns (albeit without a clear sense as to the direction in which they might affect our estimates) in inferring the extent of demand-side competition in healthcare compared to manufacturing from comparisons of productivity dispersion in the two sectors. There are important comparability differences in the measurement of productivity—such as differences in the output definition (survival versus revenue) and how inputs are measured. For instance, to directly compare the productivity dispersion metrics above, one has to view a given percentage variation in days survived after a heart attack as quantitatively analogous to the same percentage variation in tons of ready-mixed concrete. Moreover, a variety of factors—of which competitive pressure is only one—may serve to reduce equilibrium productivity dispersion in a given sector. Finally, our analysis here is limited to one specific healthcare condition (AMI).

In related work (Chandra et al. 2015), we present additional, complementary evidence suggesting that the healthcare sector may be subject to standard demand-side competitive forces. There, we look at four different conditions—AMI, congestive heart failure, pneumonia, and hip and knee replacements—that together account for almost one-fifth of Medicare hospital admissions and hospital spending. We ask whether higher quality hospitals attract greater market share at a point in time, and whether they grow more over time. A relationship between productivity and market share has been analyzed extensively in a variety of industries and countries as a proxy for the role of competition in these settings; intuitively, competitive forces exert pressure on lower productivity firms, causing them to either become more efficient, shrink, or exit.

We find robust evidence of market reallocation to higher quality hospitals across clinical outcomes-based hospital performance measures (survival and readmission) and process-of-care-based measures (i.e., adherence to well-established practice guidelines). Importantly, this positive correlation between quality and market share is systematically and substantially stronger for patients with the same condition who have more scope for choice (i.e., patients who are transfers from other hospitals rather than arrivals via the emergency room).

Our combined results suggest that, contrary to the long tradition of “healthcare exceptionalism”

in health economics, the healthcare sector may have more in common with “traditional” sectors subject to standard market forces than is often assumed. Of course, a given amount of productivity variation or a given level of allocation to higher quality producers may be more greatly valued in healthcare than in manufacturing, not to mention of greater consequence for public sector budgets. It is arguably these features of healthcare that make it exceptional.

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