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State Health Inefficiencies

Ken Sagynbekov, Marlon Graf, and Perry Wong
with Ross DeVol

HEALTH

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EXECUTIVE SUMMARY

A quarter of Americans buy unnecessary goods simply because they are on sale.[1] Americans love a bargain, but this inclination does not appear to extend to health care. Despite spending more than any other country on health, the U.S. has a mediocre ranking across most indicators.[2] According to a report published in 2012 by the Institute of Medicine, the U.S. wastes roughly one-third of health expenditures ($750 billion annually) on unnecessary medical services, costly paperwork, fraud, and poor quality services.[3] The expensive nature of the U.S. health care system has been acknowledged widely. However, our understanding of sources of inefficiencies and policies capable of addressing these areas, and ultimately providing Americans with affordable, high-quality health care, remain limited.

There are numerous studies that compare the U.S. health care system to other countries, but such comparisons are inappropriate. In effect, comparing countries like Denmark to the U.S. is no different than comparing apples to oranges. In other words, differences in estimated health care system efficiencies across countries are heavily driven by country-specific unobserved factors, which undermine the validity of lessons learned from such a comparison. In this study, we therefore choose U.S. states as our primary unit of analysis. Comparing states minimizes the effect of strong confounding factors observed in cross-country studies and allows us to draw meaningful policy conclusions. Specifically, our analysis contributes to the understanding of health care inefficiencies in the U.S. in three important ways:

First, we rank states according to their health care system efficiency scores, which we estimate using a Bayesian Stochastic Frontier Model. Although there already are numerous reports that rank

[1] "America's Bargain-hunting habits: what shoppers will and won't do to save a buck," Consumer Reports National Research Center, 2013. http://www.consumerreports.org/cro/news/2014/04/america-s-bargain-hunting-habits/index.htm.

[2] OECD. 2015. "Health at a Glance 2015." OECD Indicators. Accessed May 12, 2017. http://www.oecd.org/health/health-at-a-glance-19991312.htm.

[3] Institute of Medicine. 2012. *Best Care at Lower Cost: The Path to Continuously Learning Health Care in America.* National Academies Press.

health care quality, delivery, and population health in states, these rankings reflect a system's effectiveness and evaluate states' performances along a predefined health dimension without accounting for differences in available resources. Our ranks, on the other hand, reflect a system's efficiency and assess states' abilities to convert their health care resources into reductions in deaths amenable to health care interventions. For example, states such as Wyoming and Montana that are often ranked below Massachusetts or Vermont in effectiveness are at the top of our efficiency ranking, suggesting that these states are getting the most out of their resources.

Second, we carry out a quasi-counterfactual exercise, where we estimate what the health care cost savings would be if each state were to operate at the efficiency level of Wyoming, our top-ranked state. The results of this exercise indicate that, on average, states can reduce the cost of health care by 38% with their existing resources, which is equivalent to $1.2 trillion annually at a national scale or a reduction in health spending from 18.2 percent to 11.3 percent of the U.S. GDP.

Third, we compare the ten most efficient states to the ten least efficient states across eleven key health policy indicators commonly associated with health system inefficiency and waste both in policy debates and academic literature. We find that the overall quality score of health care systems in the most efficient states is 25% higher than that of the bottom states. In addition, per capita Medicare standardized risk-adjusted costs are 50% lower for the top states compared to the bottom, per capita community social workers are 51% higher for the top states compared to the bottom states, and the rate of uninsured is 22% lower for the top states compared to the bottom states. In other words, we find that more efficient states have fewer uninsured individuals, less wasteful spending, better quality services, and greater reliance on community social workers to bridge the gap between clinicians and patients.

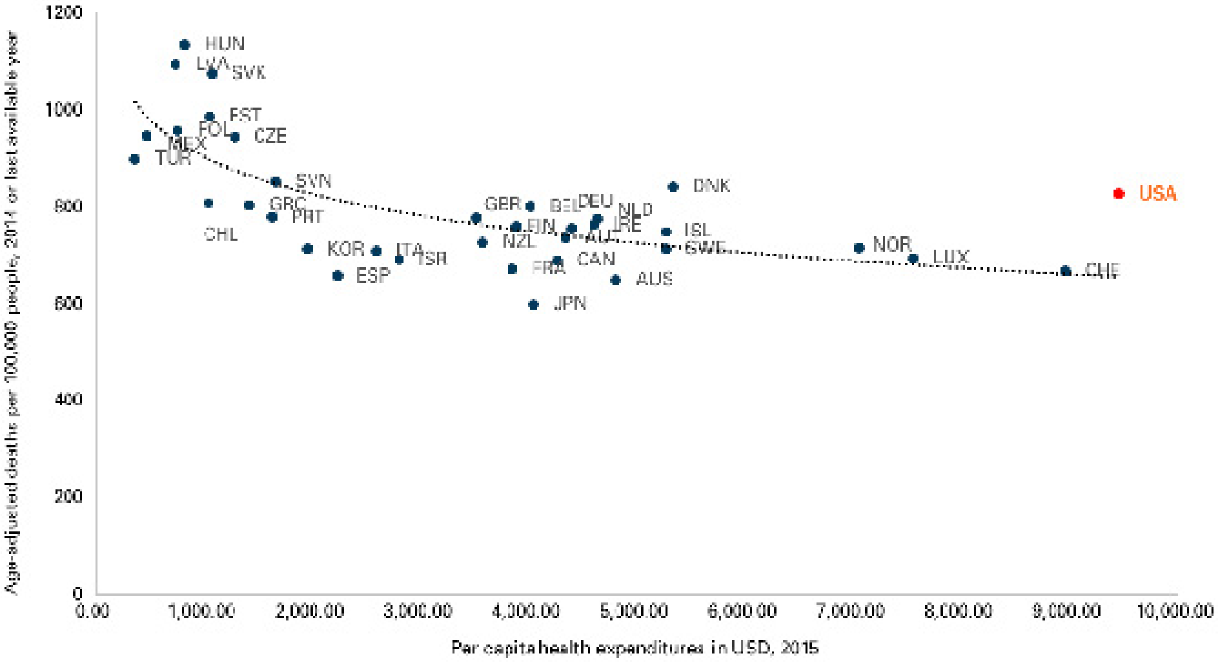
INTRODUCTION

When looking at health care expenditures and health outcomes across OECD countries, the United States consistently underperforms: its per-capita health expenditures far exceed most other member states' spending on health care systems, while the resulting health outcomes are on par with the OECD average. As illustrated in Figure 1 below, there appears to be a strong inverse relationship between per capita health expenditures and mortality rates, meaning that countries with higher expenditures exhibit lower mortality rates. The United States, however, presents an outlier to this general trend. The trend depicted in Figure 1 below has been described and replicated on various occasions by the Economist,[4] Anderson et al.,[5] and others, using a variety of health measures such as life expectancy, disability-adjusted life years, healthy life expectancy and mortality, but the main message appears to be very consistent: the United States is less effective at converting health expenditures into desirable health outcomes than most other OECD member countries.

[4] The Economist. 2015. "America's big spending on health care doesn't pay off." November 16. Accessed May 12, 2017. http://www.economist.com/news/21678669-americas-big-spending-health-care-doesnt-pay.

[5] Anderson, Gerard F., Peter S. Hussey, Bianca K. Frogner, and Hugh R. Waters. 2005. "Health spending in the United States and the rest of the industrialized world." *Health Affairs* 24 (4): 903-914.

Figure 1. Age-Adjusted Mortality per 100,000 vs. Per-Capita Health Expenditures in OECD Countries



INTRODUCTION

To underline this argument, Garber and Skinner estimate that 20-30% of U.S. health expenditures are related to inefficiency, thus reflecting unnecessary expenses.[6] The reasons for this apparent inefficiency of the U.S. health care system have been the subject of heated debates both among policymakers and academic researchers. To help inform the discussion, Hussey and colleagues conducted a systematic review to identify measures that can be used to quantify health care inefficiencies.[7] While there have been numerous attempts to evaluate and compare health care quality, there has been a lack of comparable efforts to assess efficiency. The authors attribute this lack of available studies to three factors: there is no unifying definition of health care efficiency; there is little knowledge about how such efficiency could be measured; and there is a relatively small evidence base compared to other critical components of the health system, such as quality of care.

Frequently, efficiency of health care is approximated by cost of care, which fails to account for quality. As outlined by the State Health Care Cost Containment Commission, efficiency means providing higher quality health care at lower costs.[8] As Hussey et al. point out, this definition poses major issues in comparing health systems, due to the fact that there is no easy way to adjust for quality of care. As displayed above in Figure 1, it is relatively straightforward to identify inefficiency: a country that spends a lot of money on health care and does not compare favorably to other countries in terms of health outcomes can be classified as inefficient. This notion of efficiency as an entity's ability to convert inputs into outputs at the lowest possible rate is often referred to as technical efficiency. However, it is inherently difficult to quantify just how efficient or inefficient a system is based solely on differences in health care practices and standards of care.

Waste is often referenced as a major driver of inefficiency in the U.S. medical system, though, as pointed out by Bentley et al., there is no systematic framework to identify and address specific sources of

[6] Garber, Alan M., and Jonathan Skinner. 2008. "Is American health care uniquely inefficient?" *The Journal of Economic Perspectives* 22 (4): 27-50.

[7] Hussey, Peter S., Han De Vries, John Romley, Margaret C. Wang, Susan S. Chen, Paul G. Shekelle, and Elizabeth A. McGlynn. 2009. "A systematic review of health care efficiency measures." *Health Services Research* 44 (3): 784-805.

[8] State Health Care Cost Containment Commission. 2014. "Cracking the code on health care costs." Accessed May 12, 2017. http://web1.millercenter.org/commissions/healthcare/HealthcareCommission-Report.pdf?utm_campaign=myemma%3A%20press%20release&utm_medium=email&utm_source=newsletter&utm_content=http%3A//web1.millercenter.org/commissions/healthcare/HealthcareCommission-Repo.

waste.[9] According to the authors, waste in the U.S. health care system occurs predominantly in the administrative, operational, and clinical domains. While the system is very complex and requires substantial bureaucratic structures to direct resources, identifying the appropriate level of administrative effort presents a major challenge to health care administrators. Thus, any administrative spending in excess of the amount necessary to achieve overall health objectives should be considered wasteful. Compared to other countries, the U.S. health care system is highly complex, leaving lots of room for inefficiency stemming from administrative waste. Secondly, Bentley and colleagues also distinguish between operational waste as providing the right service, but not in the most efficient way, and clinical waste as providing the wrong service in lieu of a cheaper or more effective treatment. Given the fee-for-service nature of the current health care system, providers have little incentive to operate efficiently as they are receiving reimbursements for all services provided, regardless of medical necessity. This constitutes a major problem, since determining operationally and medically appropriate and efficient modes of care is a highly context-specific task. While some regions may have cheaper and more effective treatments available, others may not. Clinical waste, on the other hand, refers to the growing tendency to treat people using more expensive and less effective methods. To an extent, this phenomenon tends to coincide with uncertain diagnoses, resulting in a willingness to test out various treatments in case one of them proves to be effective.

Aside from wasteful deployment of resources, insurance coverage and access, overuse of emergency services, as well as unhealthy dietary habits and the resulting rise in the prevalence of chronic diseases have been identified as major drivers of U.S. health care inefficiency. Specifically, Joumard et al. posit that measuring the efficiency of health systems requires an overarching objective, such as health improvement, increased access, equity and fairness, quality of care or any other measurable goal that can be used to

[9] Bentley, Tanya GK, Rachel M. Effros, Kartika Palar, and Emmett B. Keeler. 2008. "Waste in the US health care system: a conceptual framework." *Milbank Quarterly* 86 (4): 629-659.

assess performance.[10] Once a standard has been established, systems can be evaluated on their capacity to achieve said standard in the cheapest, most cost-effective way.

[10] Journard, Isabelle, Christophe André, and Chantal Nicq. 2010. "Health care systems: efficiency and institutions." Paris: Organisation for Economic Co-operation and development.

BACKGROUND

Given the steep growth in health care spending over the past decades, paired with aging populations in most OECD countries and the rise of long-term, expensive medical care practices, there has been a growing interest by both policy and academic research communities in identifying efficient health systems across the world that can serve as benchmarks and best practices to improve overall efficiency.

In a pioneering effort, Evans et al. use a longitudinal panel on 191 countries from the World Health Organization (WHO)'s World Health Report to estimate health system efficiencies between 1993 and 1997. Specifically, the authors apply a stochastic frontier method to determine potential healthy life expectancy levels, given each country's per capita health expenditures and average educational attainment. Effectively, as part of this approach, a production possibility frontier is estimated, outlining each country's maximum potential health outcomes, while controlling for its specific resources, demographic, and socio-economic covariates. While the authors admit that other factors aside from educational attainment might influence health system efficiency, they contend that education serves as a sound approximation of a broad range of factors.[11] As its main result, the study presents a ranking of health care efficiencies for WHO member countries, ranging from 99% efficiency for the most efficient countries to 1% efficiency for the lowest performers. However, as pointed out by Greene and others, comparing health systems across all WHO members is problematic for several reasons.[12] While the World Health Report provides a rich data source, quality of data and data collection procedures differ substantially between member countries, therefore calling into question the reliability of specific estimates. Moreover, using a production possibility framework to estimate efficiency requires the

[11] Evans, David B., Ajay Tandon, Christopher JL Murray, and Jeremy A. Lauer. 2000. "The comparative efficiency of national health systems in producing health: An analysis of 191 countries." Geneva: World Health Organization.

[12] Greene, William. 2004. "Distinguishing between heterogeneity and inefficiency: stochastic frontier analysis of the World Health Organization's panel data on national health care systems." *Health Economics* 13 (10): 959-980.

ability to distinguish between heterogeneity and country-specific inefficiency in converting inputs into health outcomes. In essence, a country's current performance in terms of a specific health measure such as healthy life expectancy is compared to its optimal projected performance, which is modeled based on a mix of country-specific covariates and comparisons with other countries in the sample. The vast difference in efficiency estimates between countries and the strong clustering by income and development stage that can be observed in the analysis carried out by Evans et al. suggests that WHO countries might be too dissimilar to apply such a technique, making it very difficult to distinguish between heterogeneity of countries and inefficiency within each specific country. To illustrate this dilemma, Evans and colleagues point to the prevalence of HIV/AIDS as a major predictor of efficiency rankings. Furthermore, the biggest gains in terms of life expectancy, infant mortality, and other key indicators are often realized by low and middle-income countries since higher income countries are typically closer to the optimal health levels and are thus unable to achieve substantial improvements. Thus, as countries approach a certain threshold or saturation point on health outcomes, additional spending and policies only have a marginal effect. While technically this means lower efficiency, it is merely an indication that health system efficiency is not comparable across low and high-income countries as they are facing vastly disparate health challenges. In his extension of the WHO analysis, Greene suggests that countries ought to be classified into sub-clusters based on common economic and cultural characteristics prior to comparing efficiencies. Interestingly, when looking exclusively at OECD member countries, Greene finds lower efficiency levels, which could be taken as an indication of waste and oversaturation of medical resources as described above.

Greene's analysis has spurred several studies aimed at comparing health care efficiency across OECD and EU members, motivated in part by the presumed higher level of homogeneity and comparability of countries.[13]

[13] Hernández de Cos, Pablo, and Enrique Moral-Benito. 2014. "Determinants of health-system efficiency: evidence from OECD countries." *International Journal of Health Care Finance and Economics* 14 (1): 69-93.; Asandului, Laura, Monica Roman, and Puiu Fatulescu. 2014. "The efficiency of healthcare systems in Europe: A data envelopment analysis approach." *Procedia Economics and Finance* 10: 261-268.; Medeiros, João, and Christoph Schwierz. 2015. "Efficiency Estimates of Health Care Systems." Directorate General Economic and Financial Affairs, Brussels: European Commission.

However, while organizations such as WHO, OECD, and the European Union have made health data far more accessible and have enabled these types of efficiency comparisons, a systematic review of health care system measurement studies by Varabyova and Mueller find that efficiency estimates and rankings are heavily dependent on the method applied and still suffer from systematic differences between countries, both in terms of cultural aspects, norms and traditions, and laws and regulations governing health care production practices and health behaviors. In addition, the authors emphasize that most health care implementation is carried out at the regional and local levels, rather than federal levels, thus placing restrictions on the credibility and reliability of country comparisons.[14]

In response, there has been a trend to estimate health care efficiencies at the sub-national level. Notably, Putzer and Jaramillo apply a data envelopment (DEA) framework to measure health care efficiency at the U.S. state level. The authors assess states' abilities to convert a series of inputs, consisting of the number of doctors per 1,000 people, the number of hospital beds per 1,000 people, and public health care expenditures per capita, into the prevention of disability-adjusted life years (DALYs). In doing so, the study finds that the most efficient states are clustered in the West and Northwest regions of the United States, while the least efficient states are located in the Southeast and Southern Midwest.[15] Further advocating for intra-country rather than cross-country estimation, Gearhart states that comparisons across national borders often fall victim to stark variation in health practices, medical competencies, and data collection standards.[16] Rather, examining efficiencies within a common framework allows those conducting the study to control for a vast number of country-specific factors and, in keeping with the logic outlined by Greene, makes it easier to distinguish between efficiency of health production and aspects related to environmental and contextual variation. Applying a hyperbolic distance function methodology to estimate each state's deviation from its minimal projected mortality rate, Gearhart finds no clear relationship between health expenditures and efficiency.

[14] Varabyova, Yauheniya, and Julia-Maria Müller. 2016. "The efficiency of health care production in OECD countries: A systematic review and meta-analysis of cross-country comparisons." *Health Policy* 120 (3): 252-263.

[15] Putzer, Gavin and Juan Jaramillo. 2016. "Comparing US state health efficiencies employing data envelope analysis." *Journal of Socialomics* 5 (4).

[16] Gearhart, Richard S. 2017. "Non-parametric frontier estimation of health care efficiency among US states, 2002–2008." *Health Systems* 6 (1): 15-32.

DATA

We believe that, in part, this lack of a systematic relationship is due to the health outcome selected by the authors. Specifically in an aging U.S. society, mortality presents an imperfect measure of health care performance as treatments in old age become increasingly costly and complicated, without corresponding health effects. We therefore argue that there is a need to employ a health measure that is more closely aligned with actual health care performance, such as mortality amenable to health care.[17] Following the methodology developed by Nolte and McKee and using mortality data from the Centers for Disease Control's WONDER database, we present amenable mortality figures for 2015 in Table 1. Amenable mortality consists of a list of causes of illnesses and health conditions that can lead to death but are treatable by health care. We believe that this measure represents a more direct assessment of health care performance than overall mortality, mainly due to the fact that it excludes a number of conditions whose outcomes are fatal regardless of health care received. As an example, all-cause mortality includes traffic fatalities and other accidents that, in our opinion, oftentimes do not directly reflect health care effectiveness. Using data from CDC Wonder, we construct our amenable mortality measure by using thirty-four primary causes of death as identified by Nolte and McKee, adjusted for relevant age groups. In 2015, the most prevalent causes in our list were various forms of malignant neoplasms and heart disease, while other causes such as measles, whooping cough, diphtheria, tetanus, and polio did not result in any deaths during the study year.

When examining amenable mortalities in 2015 by U.S. state and relating our primary health outcome measure to per-capita health care expenditures, we find a similar pattern as displayed above in Figure 1 for OECD countries and all-cause mortalities. As shown in Figure 2, a very strong inverse relationship exists between amenable

[17] Nolte, Ellen, and Martin McKee. 2004. "Does health care save lives? Avoidable mortality revisited." *The Nuffield Trust*; Tobias, Martin, and Li-Chia Yeh. 2009. "How much does health care contribute to health gain and to health inequality? Trends in amenable mortality in New Zealand 1981–2004." *Australian and New Zealand Journal of Public Health* 33 (1): 70-78; Schoenbaum, Stephen C., Cathy Schoen, Jennifer L. Nicholson, and Joel C. Cantor. 2011. "Mortality amenable to health care in the United States: The roles of demographics and health systems performance." *Journal of Public Health Policy* 32 (4): 407-429.

mortalities and health care spending, with some notable outliers. Residents of Utah appear to spend relatively small amounts of money on health care, while showing low levels of amenable mortalities. Presumably, this outcome could be related to lower prevalence of unhealthy behaviors such as drinking and smoking. On the other end of the spectrum, residents in the District of Columbia appear to spend a lot on their health care, while also displaying higher amenable mortalities, thus diverging from the national trends. However the most interesting takeaway from Figure 2 is the fact that while the United States health care system might seem very inefficient in comparison with its OECD peers, the more nuanced state-by-state picture reveals that the story is more complicated. It indeed appears that, in most states, higher per-capita health care expenditures are strongly correlated with fewer avoidable deaths, bearing the question why, on aggregate, the United States look as inefficient as outlined above.

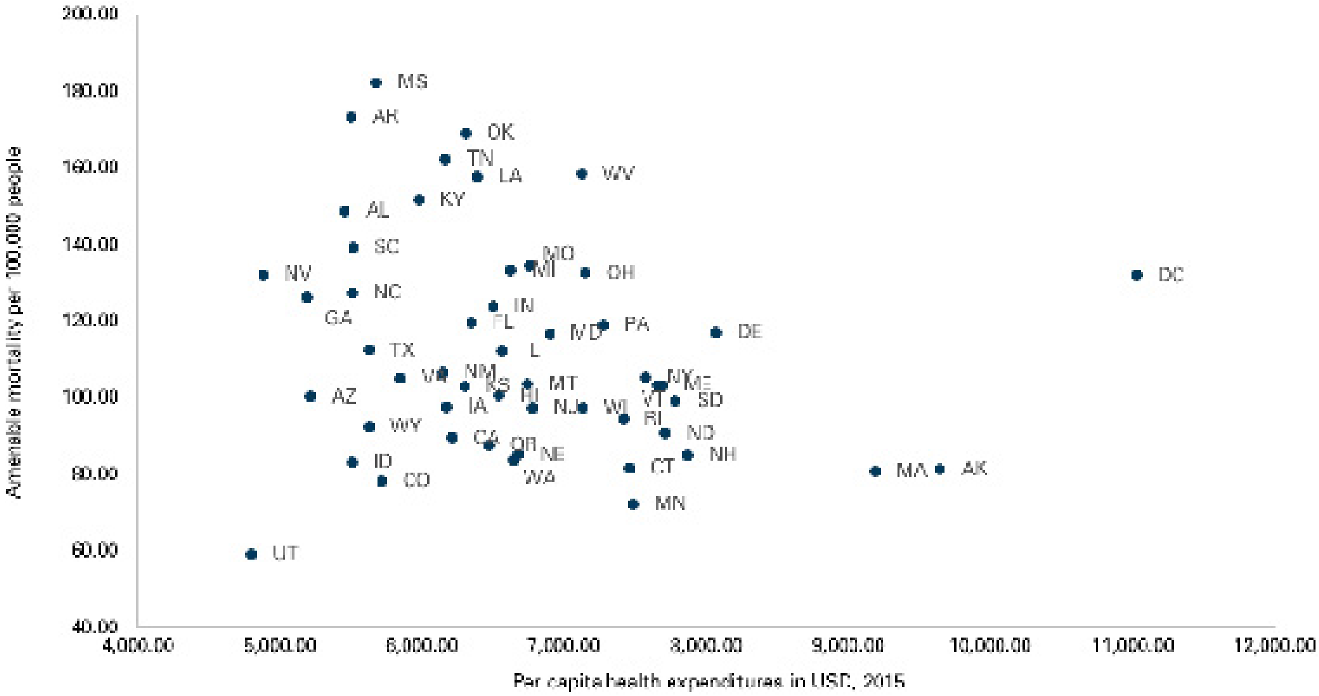
In order to systematically shed light on this research question, we calculate production frontiers and efficiency scores for all states in the following section. In the subsequent sections, we attempt to identify common factors of both efficient and inefficient states in order to delineate what drives health system efficiencies, as well as their ability to convert health inputs into better health outcomes.

Table 1. Mortality Amenable to Health Care, National-Level Crude Deaths in 2015

Disease	ICD 10	Age Group	Mean	St. Dev.	Min.	25th Perc.	Median	75th Perc.	Max.
Intestinal infections	A00-A09	0-14	3	6	0	0	0	0	18
Tuberculosis	A15-19, B90	0-74	3	10	0	0	0	0	56
Other infectious diseases (Diphtheria, Tetanus, Polio)	A35-36, A80	0-74	0	0	0	0	0	0	0
Whooping cough	A37	0-14	0	0	0	0	0	0	0
Septicemia	A40-41	0-74	365	392	16	66	220	523	2198
Measles	B05	1-14	0	0	0	0	0	0	0
Malignant neoplasm of colon and rectum	C18-21	0-74	580	607	48	140	402	709	3023
Malignant neoplasm of skin	C44	0-74	34	37	0	11	24	43	175
Malignant neoplasm of breast	C50	0-74	522	562	42	123	367	599	2929
Malignant neoplasm of cervix uteri	C53	0-74	68	83	0	15	47	87	422
Malignant neoplasm of cervix uteri and body of the uterus	C54-55	0-44	1	5	0	0	0	0	30
Malignant neoplasm of testis	C62	0-74	4	11	0	0	0	0	55
Hodgkin's disease	C81	0-74	11	17	0	0	0	16	83
Leukemia	C91-95	0-44	30	42	0	0	20	36	234
Diseases of the thyroid	E00-07	0-74	8	14	0	0	0	12	62
Diabetes mellitus	E10-14	0-49	59	59	0	18	45	86	299
Epilepsy	G40-41	0-74	36	40	0	11	27	45	202
Chronic rheumatic heart disease	I05-09	0-74	23	23	0	11	17	28	117
Hypertensive disease	I10-13, I15	0-74	642	754	34	106	416	828	3710
Ischemic heart disease	I20-25	0-74	2816	2933	272	603	2159	3351	13704
Cerebrovascular disease	I60-69	0-74	803	856	60	192	583	954	4162
All respiratory diseases (excl. pneumonia and influenza)	J00-09, J20-99	1-14	6	9	0	0	0	12	41
Influenza	J10-11	0-74	24	22	0	11	21	32	99
Pneumonia	J12-18	0-74	293	308	0	91	221	353	1522
Peptic ulcer	K25-27	0-74	26	34	0	0	19	33	200
Appendicitis	K35-38	0-74	1	4	0	0	0	0	23
Abdominal hernia	K40-46	0-74	13	17	0	0	12	17	86
Cholelithiasis and Cholecystitis	K80-81	0-74	20	25	0	0	16	28	136
Nephritis and Nephrosis	N00-07, N17-19, N27-27	0-74	358	380	14	76	200	507	1836
Benign prostatic hyperplasia	N40	0-74	0	0	0	0	0	0	0
Maternal deaths	O00-99	all	20	30	0	0	11	32	157
Congenital cardiovascular anomalies	Q20-28	0-74	230	244	12	61	174	267	1132
Perinatal deaths, all causes excluding stillbirths	P00-96, A33-34	All	53	62	0	17	40	62	320
Medical malpractice	Y60-69, Y83-84	All	41	40	0	11	32	56	178

Source: Methodology adapted from Nolte & McKee 2004; data obtained from CDC Wonder

Figure 2. Amenable Mortality and Health Care Expenditures (2015)



METHODOLOGY

Inefficiency in production simply refers to a percentage difference between an observed amount of output and an unobservable (but potentially feasible) maximum amount of output that can be produced with the same amount of inputs. For example, if for a certain amount of inputs a potentially feasible quantity of output is 10 but a firm produces only 9, the inefficiency score is 0.1 and the efficiency score is 0.9, which indicates that the firm is producing 10% below the maximum feasible level. Although inefficiency, in theory, is an intuitive concept, the fact that we do not observe potentially feasible maximum amounts of output corresponding to different levels of inputs poses a number of practical challenges. In this section, we outline these challenges and describe how we address them.

A BLACK BOX OF PRODUCTION

A production process describes how inputs are transformed into outputs. A production technology is essentially a black box that governs the matching of inputs to outputs. From a mathematical perspective, a production technology is a collection of input-output pairs. Given this technological environment, a firm chooses a particular input-output pair. One of the key assumptions behind all efficiency analyses is that all firms face an identical or a similar technological environment. In other words, all input-output combinations available to one firm should also be available to any other firm. If two firms operate under different technological environments, each firm will have differing potentially feasible maximum outputs or production frontiers. This, in turn, would suggest that comparing inefficiency scores makes no economic sense, since a potentially attainable output level for one firm may be unattainable for another.

Greene's concerns that the cross-country efficiency estimates from the World Health Report do not distinguish between country-specific heterogeneity and efficiency[18] and Varabyova and Mueller's observation that the variation in cross-country efficiency estimates are likely to be confounded by country-specific contextual factors[19] are different ways of saying that technological environments across countries are too dissimilar for any meaningful comparison of efficiency. Thus, in this paper, we share Gearhart's position that a state-level comparison of efficiencies in health care delivery systems provides a more suitable analytical framework and context.[20] However, our methodological approach, which we describe in the following sections, substantively differs from that used by Gearhart.

INPUTS, OUTPUTS, AND CONTEXTUAL FACTORS IN THE HEALTH CARE DELIVERY SYSTEM

Most studies of health care delivery system efficiency, including the Gearhart study, use the age-standardized mortality rate or the life expectancy at birth as measures of health care delivery system output. Although these indicators are appropriate measures of overall population health, they are influenced by a long list of factors outside of the health care delivery system. We agree with Allin and Grignon's argument that "a valid performance indicator of health system effectiveness should be sensitive to health system interventions."[21] Consequently, we use amenable mortality as our primary measure of health care delivery system output, because it only counts deaths that have been shown to be amenable to health system interventions.

We use population- and age-adjusted number of physicians and nurses, hospital beds, and health care expenditure as inputs in the health care delivery system as measures of labor, as well as physical and financial capital. We exclude contextual variables from the first stage of estimation. In the second stage of estimation, we explore statistical associations between efficiency scores and a myriad of

[18] Greene, William. 2004. "Distinguishing between heterogeneity and inefficiency: stochastic frontier analysis of the World Health Organization's panel data on national health care systems." *Health Economics* 13 (10): 959-980.

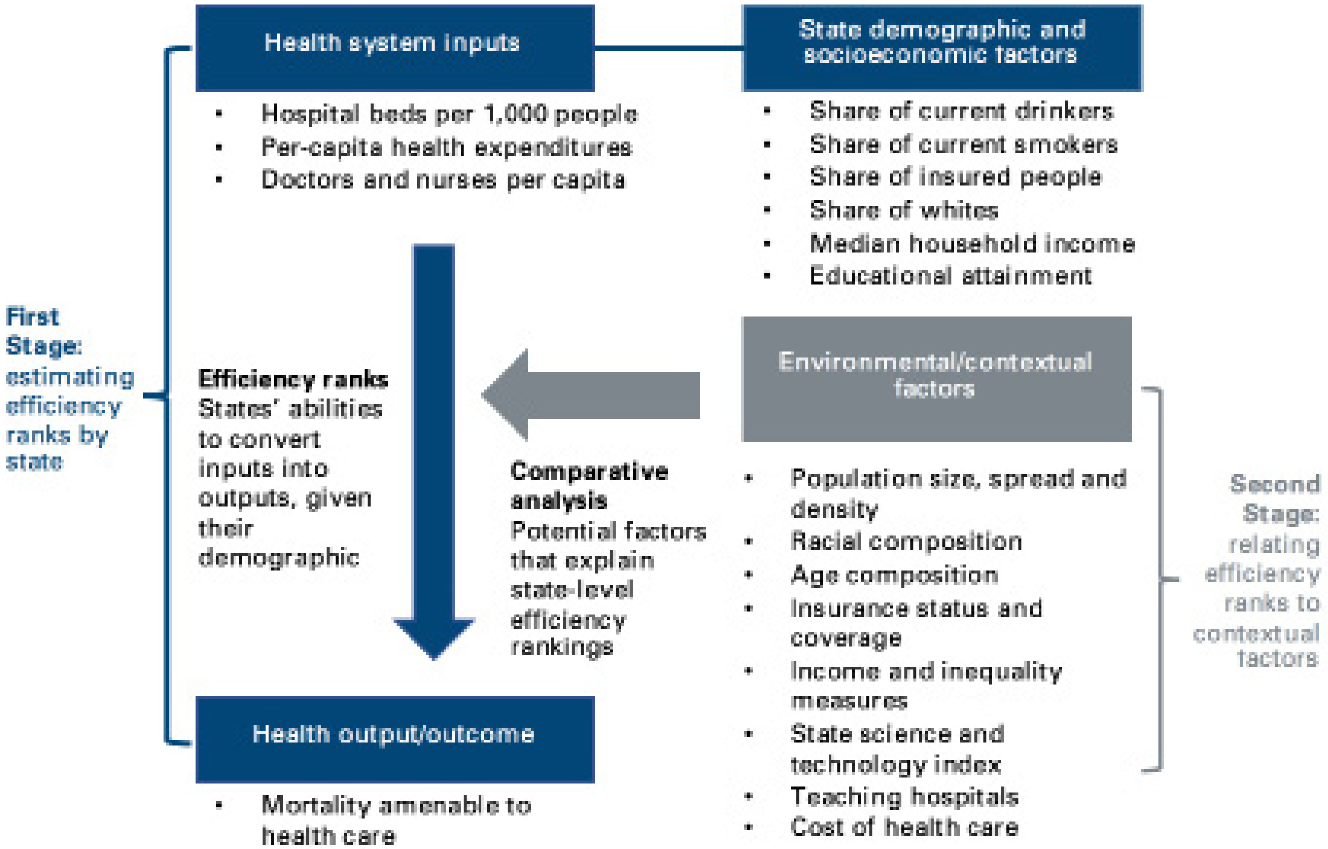
[19] Varabyova, Yauheniya, and Julia-Maria Müller. 2016. "The efficiency of health care production in OECD countries: A systematic review and meta-analysis of cross-country comparisons." *Health Policy* 120 (3): 252-263.

[20] Gearhart, Richard S. 2017. "Non-parametric frontier estimation of health care efficiency among US states, 2002–2008." *Health Systems* 6 (1): 15-32.

[21] Allin, Sara, and Michel Grignon. 2014. "Examining the role of amenable mortality as an indicator of health system effectiveness." *Healthcare Policy* 9 (3): 12.

contextual factors. Figure 3 depicts the conceptual design that we use to guide our empirical analysis.

Figure 3. Logic Model



PRODUCTION FRONTIER

An input-output pair or a production plan is said to be efficient if it lies on the production frontier, which we do not observe but extrapolate from observed combinations of inputs and outputs. To the best of our knowledge, almost all empirical studies use either Data Envelopment Analysis (DEA) or Stochastic Frontier Analysis (SFA) methods to construct said production frontier. We refer readers to Bogetoft and Otto, Jacobs, Smith, and Street, and Coelli et al. for a detailed treatment of each of these methods and their applications.[22] In this section, we briefly outline key characteristics of

[21] Bogetoft, Peter and Lars Otto. 2010. *Benchmarking with DEA, SFA, and R.* Springer Science & Business Media; Jacobs, Rowena, Peter C. Smith and Andrew Street. 2006. *Measuring Efficiency in Health Care: Analytic Techniques and Health Policy.* Cambridge University Press; Coelli, Timothy J., Dodla Sai Prasada Rao, Christopher J. O'Donnell, and George Edward Battese. 2005. *An Introduction to Efficiency and Productivity Analysis.* Springer Science & Business Media.

both techniques and explain why we prefer SFA over DEA for the purpose of estimating state-level health care delivery system efficiency scores.

DEA is a non-parametric approach that uses a linear programming procedure to construct the production frontier. It treats outermost input-output pairs as lying on the frontier and generates efficiency scores for each decision unit (a particular state in our application) by only using information from comparable units. Since the construction of the frontier depends only on the data at hand, this approach requires minimum a priori assumptions (modeling flexibility) about the functional form of the production function. Furthermore, in reality, most firms produce multiple outputs, a scenario that is easily handled by DEA. However, despite its many advantages, DEA also has several drawbacks; notably, the technique assumes that the production relationship is correctly specified (no relevant inputs or outputs are missing in the specification) and that all input-output pairs are deterministic (given the same input mix, we should be able to get exactly the same quantity of output). Lastly, a major criticism of DEA is that the location of the production frontier is sensitive to outliers. Gearhart's use of the hyperbolic order-- estimator, a modified version of DEA that estimates conditional quantiles of order-- in the neighborhood of true production frontier, alleviates the problem of outliers while preserving all the advantages built in the DEA technique.[23]

SFA, in contrast, is a parametric method that uses statistical modeling to construct the production frontier. Compared to DEA, SFA is less flexible in the sense that it requires strong assumptions about the functional form of how inputs relate to output. Furthermore, one has to impose additional assumptions about the distribution of the inefficiency term. As with any statistical modeling, SFA is also sensitive to outliers, multicollinearity, heteroscedasticity, and small sample size. Despite these shortcomings, however, SFA holds several substantive advantages over DEA. First, the stochastic

[23] Gearhart, Richard S. 2017. "Non-parametric frontier estimation of health care efficiency among US states, 2002–2008." *Health Systems* 6 (1): 15-32.

nature of SFA distinguishes between random noise and inefficiency terms, a feature that DEA does not have. The importance of this might not be readily apparent when we think of a traditional economic examples of a firm producing a product, say a component of a car. In this example, if a firm produces 100 components with 10 machine operators and 10 machine hours today, there is no a priori expectation that with the same input hours the number of components would be different than 100 next year. Now, if we were to replace car components with the mortality rate, and machine operator and machine hours with physician hours and hospital beds, it is no longer safe to assume that the mortality rate would be the same next year. Mortality rates are influenced by many factors, though some more than others. Therefore, assuming a deterministic relationship between health care delivery system inputs and output is unrealistic. Second, the way SFA determines the shape of the frontier is guided by economic theory. Since SFA relies on economic theory, production function parameter estimates are readily interpretable and testable, which is not the case when DEA is used. Third, SFA's stochastic nature provides a modeling flexibility to account for technological heterogeneity, another feature that is missing in DEA.

A BAYESIAN STOCHASTIC FRONTIER MODELING

In this study, we use a Bayesian framework to estimate SFA parameters and inefficiency scores. The approach has two important advantages over the traditional maximum likelihood method. Zhang shows that the Bayesian estimator of efficiency scores has a lower mean square error (MSE) than that of the maximum likelihood estimator, where a smaller MSE indicates a greater accuracy.[24] Furthermore, in contrast to the maximum likelihood estimator, which relies on asymptotic properties (an unrealistic assumption when working with a small dataset), the Bayesian estimator is capable of generating reasonable uncertainty bounds around point estimates of efficiency scores using the data at hand.

[24] Zhang, Xingyuan. 2000. "A Monte Carlo Study on the Finite Sample Properties of the Gibbs Sampling Method for a Stochastic Frontier Model." *Journal of Productivity Analysis* 14 (1): 71-83.

The model has the following form:

$$y_i = h(x_i, \beta) + \varepsilon_i - u_i \quad (1)$$

$$\bar{y}_i = h(x_i, \beta) + \varepsilon_i \quad (2)$$

$$h(x_i, \beta) = \alpha + \beta_1 Labor_i + \beta_2 Physical\ Capital_i + \beta_3 Financial\ Capital_i \quad (3)$$

$$y_i \sim N(h(x_i, \beta) - u_i, \sigma_\varepsilon^2) \quad (4)$$

$$u_i \sim N^+(\varphi, \sigma_u^2) \quad (5)$$

$$\varphi \sim N(0, 0.001) \quad (6)$$

$$\beta_i \sim N(0, 0.000001) \quad (7)$$

$$\alpha \sim N(0, 0.000001) \quad (8)$$

We model the log of amenable mortality in state i, y_i, as a function of production inputs, h(x_i,-), an inefficiency term, u_i, and a random disturbance term, -_i (equation 1). The frontier is defined by equation 2. The h(x_i,-) term consists of labor, physical, and financial inputs, which we measure by the sum of per capita physicians and nurses, per capita hospital beds, and per capita health care expenditure (equation 3). Although most studies age-standardize their dependent outcome variable, Rosenbaum and Rubin show that, unless the right hand side variables are also age-standardized, the estimated parameters will be biased. Instead, they suggest regressing the unadjusted dependent variable on unadjusted right hand side variables, where the resulting age category variables will lead to unbiased parameter estimates.[25] In our data analysis, we follow this procedure and include five age groups. We further assume that the inefficiency term follows a truncated normal distribution (equation 5). Although there are many alternative distributions that generate positive values such as half-normal, exponential, log-normal, Gamma, generalized Gamma, and Weibull, Ehlers' Monte Carlo simulation based comparison of various distributions rates the truncated-normal distribution consistently higher than all other alternatives.[26] We use relatively vague priors for all model parameters (equations 6-8) and run three chains with 500,000 iterations per chain (dispose of 100,000 iterations as burn-in observations). The estimation was carried out on JAGS platform version 4.2.0 and rjags package in R version 3.2.4 to obtain posterior parameter estimates.

[25] Rosenbaum, Paul R., and Donald B. Rubin. 1984. "Difficulties with regression analyses of age-adjusted rates." *Biometrics* 437-443.

[26] Ehlers, Ricardo S. 2011. "Comparison of Bayesian models for production efficiency." *Journal of Applied Statistics* 2433-2443.

RESULTS

Table 2 shows population and age structure adjusted output elasticities with respect to health care delivery system inputs and the estimates of efficiency scores for each state. Since the model specification (equation 1) is a reformulation of a multiplicative Cobb-Douglas production function (equation 9), estimated coefficients (partial output elasticities) are not affected by technical efficiency (equation 10).

$$y = h(x_i, \beta)e^{-u}e^{\varepsilon} \quad (9)$$

$$\frac{\partial y}{\partial x_i}\frac{x_i}{y} = \frac{\partial h(x_i,\beta)}{\partial x_i}e^{-u}\frac{x_i}{h(x_i,\beta)e^{-u}} = \beta_i \quad (10)$$

The amenable mortality variable and input variables are expressed in standardized natural log units. The estimated output elasticity with respect to physicians and nurses is -0.37 (95% Confidence Bounds: -0.84 and 0.09), which indicates that a one percent increase in health care delivery labor force is associated with 0.37 percent reduction in amenable mortality. The output elasticity estimate for hospital beds, however, shows a positive association with the amenable mortality variable. This result reflects the fact that the quantity of per capita hospital beds is a poor proxy for physical capital, since it represents both supply (a physical space to treat patients that leads to lower mortality) and demand (a less healthy population requires more space and leads to higher mortality) sides of health care system. A positive sign of this coefficient suggests that hospital beds variable captures states' population health status rather than the availability of physical assets needed to treat patients. The choice of using hospital beds as a proxy to physical capital was partly driven by our inability to find data for a more appropriate variable such as the number of diagnostic devices, and partly by the fact that it is a commonly used variable in most of the health care system efficiency literature.

The financial capital variable, a stock measure that we approximate using per capita health care expenditures, shows both a practically meaningful and statistically significant association with the rate of amenable mortality. We find that a one percent increase in per capita health care expenditure is associated with roughly half a percent reduction in amenable mortality (95% Confidence Bounds: -0.86 and -0.09).

In addition to output elasticities with respect to individual inputs, the model allows us to calculate elasticities of scale by adding up input coefficients. For example, if both labor and financial capital inputs were to increase by 10 percent, all else equal, the rate of amenable mortality would decrease by 8.5 percent.

Table 2 also shows how a state's age composition relates to amenable mortality. The data indicates that the rate of amenable mortality is lowest among the age groups 0-14 and 75 and older and highest in the 60-74 age group.

The estimated medians of technical efficiency scores for states range from the lowest value of 83% for Oklahoma to the largest values of 91% for Montana and Wyoming. The estimates of efficiency scores indicate that health care delivery systems in all states are operating near the production frontier. Although health care delivery system resources vary substantially across states, states do not appear to differ dramatically in terms of how effectively they convert services of physicians and nurses and spending on health care into reductions in preventable deaths. Furthermore, large uncertainty bounds suggest that median efficiency scores for adjacent states in Figure 4 are statistically indistinguishable from each other. This is hardly surprising, since the standard deviation of the error term is 13 times larger than that of the efficiency term, which indicates that only a small fraction of the cross-state variation in amenable mortality is attributable to differences in technical efficiency. Despite a narrow range in efficiency scores and large uncertainty bounds, our quasi-counterfactual exercises described in the next section suggest that small improvements in efficiency have the potential to substantially reduce avoidable deaths and health care costs.

Table 2. SFA Model Estimates of Health System Efficiency

Variables	Median	Mean	Std. Err.	95% CI		Variables	Median	Mean	Std. Err.	95% CI	
Intercept	-0.18	-0.20	0.17	-0.60	0.07	Share of people aged 30-44	0.38	0.38	0.18	0.02	0.74
Doctors and nurses per 1000 people	-0.37	-0.37	0.24	-0.84	0.09	Share of people aged 45-59	0.62	0.62	0.21	0.22	1.03
Hospital beds per 1000 people	0.84	0.84	0.16	0.53	1.15	Share of people aged 60-74	0.66	0.66	0.23	0.21	1.10
Health expenditure per capita	-0.48	-0.48	0.20	-0.86	-0.09	Share of people aged 75+	-0.01	-0.01	0.21	-0.43	0.40
Share of people aged 15-29	0.47	0.47	0.27	-0.06	0.99						
Alabama	0.87	0.84	0.14	0.46	0.99	Montana	0.91	0.88	0.10	0.62	1.00
Alaska	0.88	0.84	0.14	0.45	0.99	Nebraska	0.89	0.86	0.12	0.56	1.00
Arizona	0.88	0.84	0.14	0.48	0.99	Nevada	0.88	0.84	0.14	0.47	0.99
Arkansas	0.85	0.81	0.17	0.35	0.99	New Hampshire	0.90	0.87	0.11	0.59	1.00
California	0.88	0.85	0.13	0.52	0.99	New Jersey	0.88	0.85	0.13	0.50	0.99
Colorado	0.90	0.88	0.11	0.60	1.00	New Mexico	0.86	0.82	0.16	0.39	0.99
Connecticut	0.89	0.86	0.12	0.56	0.99	New York	0.88	0.85	0.13	0.50	0.99
Delaware	0.84	0.79	0.18	0.30	0.99	North Carolina	0.86	0.82	0.15	0.40	0.99
District of Columbia	0.87	0.83	0.15	0.41	0.99	North Dakota	0.90	0.87	0.11	0.59	1.00
Florida	0.88	0.84	0.14	0.48	0.99	Ohio	0.85	0.80	0.17	0.34	0.99
Georgia	0.88	0.85	0.13	0.50	0.99	Oklahoma	0.83	0.77	0.19	0.25	0.99
Hawaii	0.86	0.82	0.15	0.41	0.99	Oregon	0.88	0.85	0.13	0.50	0.99
Idaho	0.89	0.85	0.13	0.52	0.99	Pennsylvania	0.87	0.83	0.14	0.45	0.99
Illinois	0.87	0.84	0.14	0.46	0.99	Rhode Island	0.88	0.84	0.14	0.48	0.99
Indiana	0.86	0.81	0.16	0.37	0.99	South Carolina	0.88	0.84	0.14	0.47	0.99
Iowa	0.89	0.86	0.12	0.54	0.99	South Dakota	0.88	0.85	0.13	0.51	0.99
Kansas	0.89	0.85	0.13	0.52	0.99	Tennessee	0.86	0.81	0.16	0.38	0.99
Kentucky	0.87	0.83	0.15	0.43	0.99	Texas	0.86	0.82	0.15	0.40	0.99
Louisiana	0.85	0.80	0.18	0.32	0.99	Utah	0.89	0.85	0.13	0.52	0.99
Maine	0.89	0.86	0.12	0.54	0.99	Vermont	0.87	0.84	0.14	0.46	0.99
Maryland	0.85	0.81	0.17	0.35	0.99	Virginia	0.89	0.86	0.12	0.53	0.99
Massachusetts	0.88	0.84	0.14	0.47	0.99	Washington	0.89	0.85	0.12	0.53	0.99
Michigan	0.86	0.81	0.16	0.38	0.99	West Virginia	0.87	0.83	0.15	0.43	0.99
Minnesota	0.90	0.87	0.11	0.57	1.00	Wisconsin	0.87	0.83	0.14	0.45	0.99
Mississippi	0.86	0.82	0.16	0.39	0.99	Wyoming	0.91	0.89	0.10	0.63	1.00
Missouri	0.86	0.81	0.16	0.38	0.99						

Figure 4. Efficiency Scores with Respect to Amenable Mortality
25th Percentile, Median, and 75th Percentile

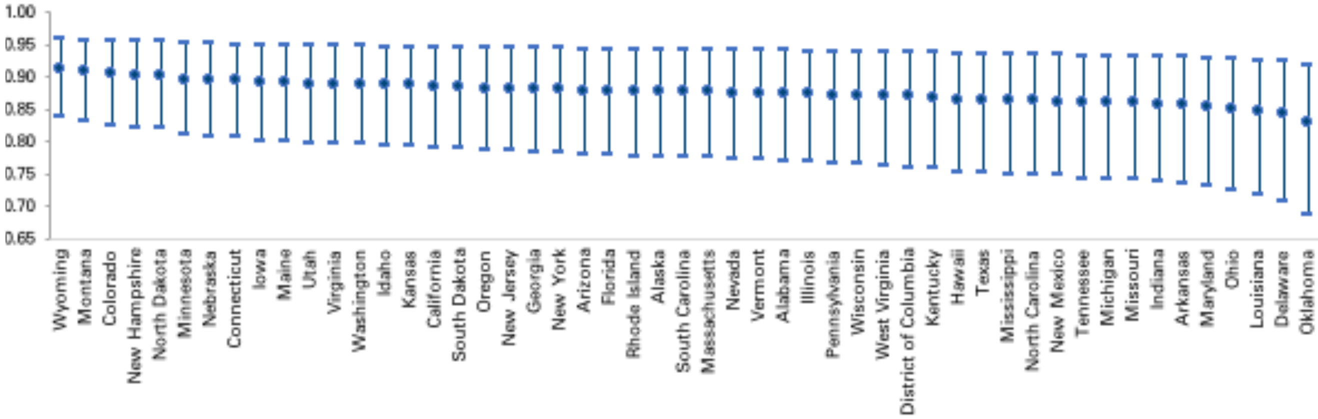
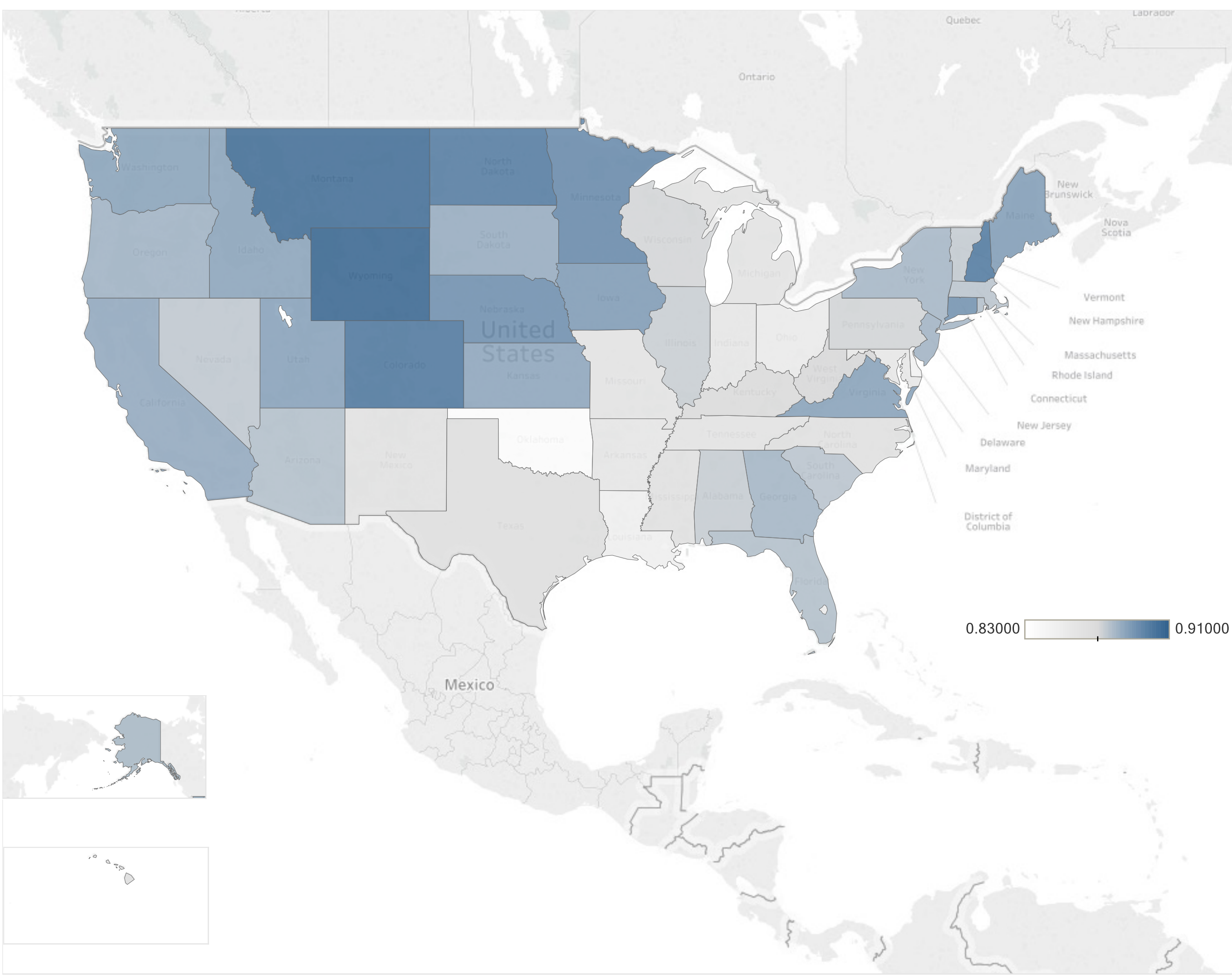


Figure 5. U.S. Map of Efficiency Scores with Respect to Amenable Mortality



POLICY IMPLICATIONS

If all states were to operate at the efficiency level observed in Wyoming, the state with the highest efficiency score, how much would each state save on health care costs? We answer this question by replacing estimated median efficiency scores for all states (Figure 4) with the efficiency score of Wyoming (0.91) and allowing per capita health care expenditure to adjust while keeping the rate of amenable mortality, the number of physicians and nurses, and the number of hospitals unchanged. The results of this quasi-counterfactual exercise are shown in Figure 6. The health care cost savings as a share of current per capita health care spending ranges from 4% in Montana to 69% in Oklahoma, with the average savings for all states of roughly 38%. To put in perspective the 38% potential reduction in health expenditures, improving efficiency can potentially save $1.2 trillion in total national health spending (CMS.gov reports that in 2015 the U.S. spent $3.2 trillion for health care), which is equivalent to an annual spending on Medicare and Medicaid combined (CBO reports $646 billion on Medicare and $545 billion on Medicaid in 2015).

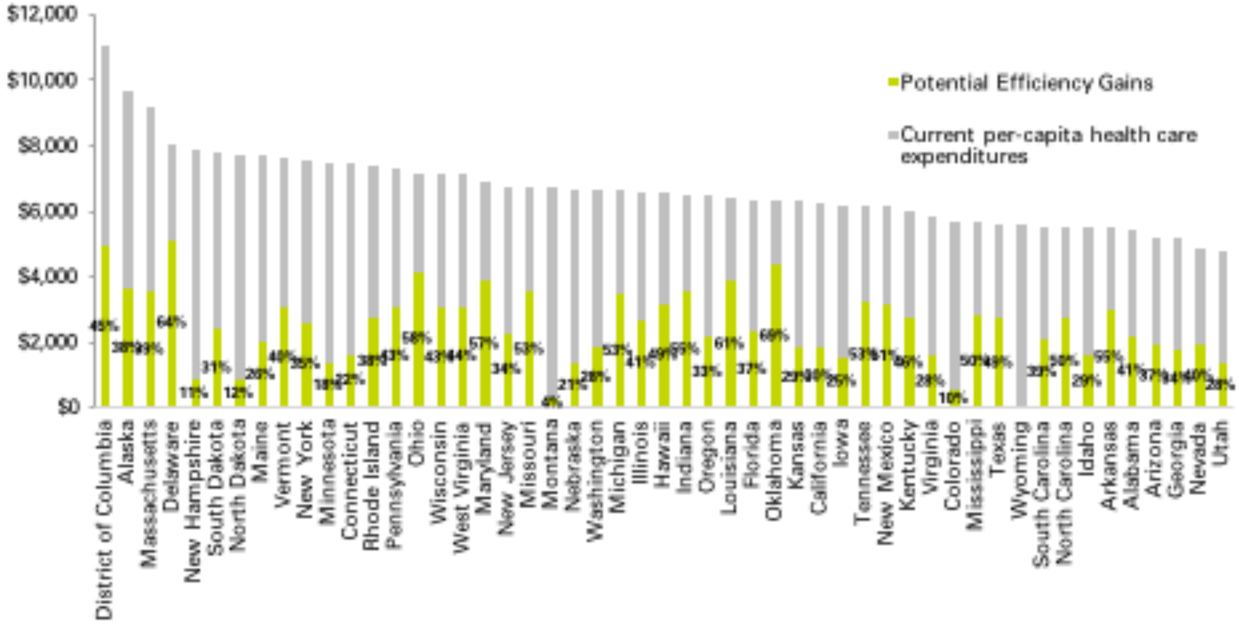
The results presented in this study differ substantively from traditional reports such as the Commonwealth Fund Scorecard on State Health System Performance, a comprehensive assessment of health care system performance across 40 indicators.[27] While these performance rankings measure *effectiveness* (output differences across states) of health care systems, our study measures *efficiency* (output differences across states after adjusting for resource availability) of health care systems. Our rankings show that states with better health outcomes do not necessarily rank high in terms of efficiency. For example, despite its lower amenable mortality rate, Massachusetts has a lower efficiency score than that of Montana (Amenable Mortality: 80 deaths vs. 104 deaths per 100,000; Efficiency Scores: 0.88 vs. 0.91). Similarly, we do not see a clear

[27] See for example: http://www.commonwealthfund.org/interactives/2017/mar/state-scorecard/.

association between per capita health expenditures and potential cost savings from improved efficiency (Figure 6).

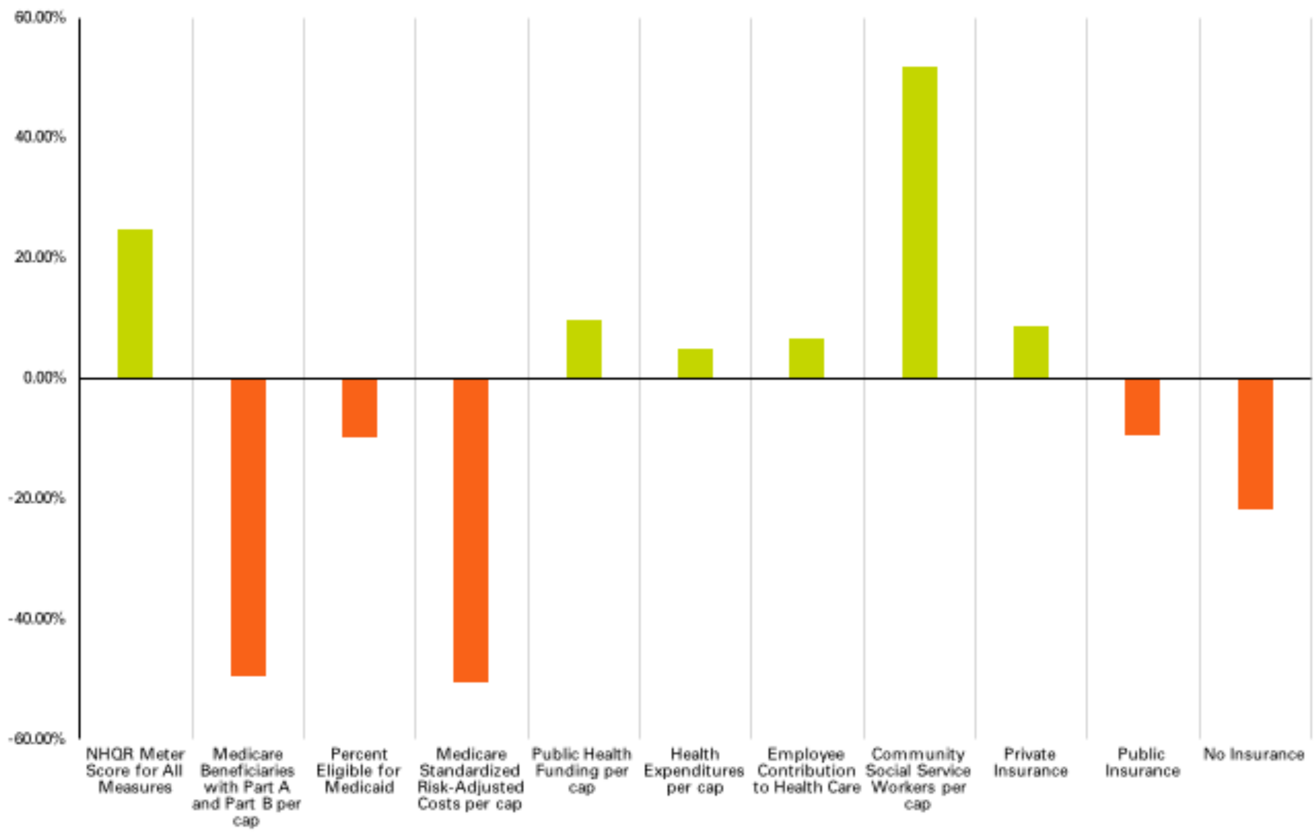
Although we cannot establish a causal link between policy choices and health care efficiency, we show how the most efficient states differ from the least efficient states along important health policy dimensions (Figure 7). We average 11 policy indicators for states ranked in both the top ten and bottom ten for efficiency and examine the difference between them. Out of 11 policy indicators, we find that five indicators show the most contrast between top and bottom states. Namely, we find that the overall quality score of health care system in the top efficient states is 25% higher than that of the bottom states, that per capita Medicare Part A and B enrollment numbers are 50% lower for the top states compared to the bottom states, that per capita Medicare standardized risk-adjusted costs are 50% lower for the top states compared to the bottom, that per capita community social workers are 51% higher for the top states compared to the bottom states, and that the rate of uninsured is 22% lower for the top states compared to the bottom states. In other words, more efficient states appear to have less uninsured individuals, a reduction in unnecessary spending, better quality services, and more reliance on community social workers to bridge the gap between clinicians and patients.

Figure 6. Potential Cost Savings from Efficiency Gains



Note: Percentage denotes relative efficiency gains = potential efficiency gains/current expenditures

Figure 7. Percentage Differences in Health System Variables Between Top 10 and Bottom 10 States in Terms of Health Care Efficiency Rankings



CONCLUSIONS

In this study we have ranked states according to their health care system efficiency scores using a Bayesian Stochastic Frontier Model. To capture the direct influence of health care system inputs, we have constructed state-by-state mortality rates amenable to health care interventions following a methodology introduced by Nolte and McKee.[28] In contrast to many existing reports that compare the *effectiveness* of health care system across states, we rank states based on their *efficiency*, meaning their ability to convert scarce health care resources into reductions of amenable mortality.

[28] Nolte, Ellen, and Martin McKee. 2004. "Does health care save lives? Avoidable mortality revisited." *The Nuffield Trust.*

The results of our data analysis indicate that the most efficient states offer higher quality health care services at lower costs, have a lower rate of uninsured, and rely more on community social workforce compared to states with the lowest efficiency scores.

However, we do caution that the estimates presented in this study must be taken with great care, as they are indeed just estimates and rest on various assumptions. Therefore, as it is true for any statistically derived number, these estimates come with a degree of uncertainty and have a number of limitations as outlined in previous sections. Despite these limitations, the results presented in this study make substantive contributions to the evidence-based health care discussion.

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ABOUT THE AUTHORS

Dr. Ken Sagynbekov is the corresponding author of this paper. As a health economist at the Milken Institute, his research focuses primarily on applied microeconomic analysis of health, with an emphasis on quantitative methods. Sagynbekov's work has been published in peer-reviewed academic journals and government reports. Before joining the Institute, he was a professor of economics at the University of Regina in Canada, where he lead a team of researchers to find practical solutions to community safety issues and served as lead investigator in several large government funded research projects. In addition to academia, Sagynbekov worked as an economic consultant in Central Asia with USAID's fiscal reform initiative. He received a B.Sc. in finance from Clemson University and earned his M.A. and Ph.D. degrees in economics from the University of Mississippi. He works at the Institute's Santa Monica office.

Dr. Marlon Graf is a health research analyst at the Milken Institute. His work focuses primarily on applied microeconomic analysis of health and substance abuse issues, with an emphasis on mixed methods research and has published in peer-reviewed journals and policy reports. Recently, he has been looking at a range of different health policy issues, such as the effects of community health programs on health outcomes, the efficiency and effectiveness of health systems across U.S. states, and the impact of ridesharing services on drunk-driving. Before joining the Institute, Graf was an assistant policy analyst at the RAND Corp. and a doctoral fellow at the Pardee RAND Graduate School, where he carried out qualitative and quantitative analyses on a wide range of policy issues, including alcohol and crime control, innovation, technology and economic growth, financial decision-making, and higher education finance. Graf holds a B.Sc. in business administration from the University of Mannheim (Germany), a master's in public policy from the UC Los Angeles, and a Ph.D. in policy analysis from the Pardee RAND Graduate School.

Perry Wong is managing director of research at the Milken Institute. He is an expert in regional economics, development, and econometric forecasting and specializes in analyzing the structure, industry mix, development, and public policies of a regional economy. He designs, manages, and performs research on labor and workforce issues; the relationship between technology and economic development; and trade and industry, with a focus on policy development and implementation of economic policy in both leading and disadvantaged regions. Wong is actively involved in projects aimed at increasing access to technology and regional economic development in California and the rest of the United States. His work extends to the international arena, where he is involved in regional economic development in greater China and other parts of Asia. Prior to joining the Institute, Wong was a senior economist and director of regional forecasting at Global Insight Inc. (formerly Wharton Econometric Forecasting Associates, Inc), where he managed regional quarterly state and metropolitan area forecasts and provided consultation. There, he designed regional modeling systems and contributed to regional economic impact studies on such topics as budget reduction and healthcare reform. Wong has conducted many research studies regarding regional economic development and policy impacts on the public and private spheres. These include the impact of U.S. budget and trade policy on key U.S.

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industries and regions; healthcare reform and its implications for the federal budget; the Kyoto Agreement and its impact on the well-being of U.S. regional economies; and the pharmaceutical industry's contribution to Pennsylvania's economy.

Ross DeVol is the former chief research officer at the Milken Institute. During his tenure as the chief research officer, DeVol oversaw research on international, national, and subnational growth performance; access to capital and its role in economic growth and job creation; and health-related topics. DeVol has put the organization in the national limelight with groundbreaking research on technology and its impact on regional and national economies and on the economic and human consequences of chronic disease. He specializes in the effects of research and development activities, international trade, human capital and labor force skills training, entrepreneurship, early-stage financing, and quality-of-place issues on the geographic distribution of economic activity. His "Best-Performing Cities: Where America's Jobs Are Created" was first published in 2004 and has been regularly updated since.

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