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STATE LEVEL EFFICIENCY MEASURES FOR HEALTHCARE SYSTEMS

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This article presents a parametric approach to healthcare system productivity analysis across the USA between 2000 and 2003. Though similar productivity analyses have been made on a country level, little research is devoted to state-level healthcare efficiency analysis. Hence, the aim of this exercise is to compute the so-called technical frontier also known as the best practice frontier which represents maximum obtainable output given inputs. The difference between each state's health level and its potentially attainable maximum denotes a given state healthcare inefficiency. The Stochastic Frontier approach used in this article allows the computation of efficiency scores as well as accounting for random disturbances in the data.

INTRODUCTION

There are several ways to consider frontier analysis and at least two of them have been applied in healthcare performance studies. These are either cost or production efficiency. The aim of cost efficiency analysis is to assess how much (minimum) cost it takes to produce output (or set of outputs) given inputs and market prices. Then by measuring the difference between the minimum cost and the observed real cost we can asses each unit's inefficiency. Those estimates carry two effects:

- Technical efficiency (deviation from "the best practice technology")
- Allocative efficiency which is concerned with price allocation (see, e.g. Greene, 2008)

Such analyses are known to have been applied to microeconomic healthcare studies such as hospital or nursing home performances benchmarks. (See Koop, Osiewalski, & Steel, 1997 or Farsi & Filippini, 2003.)

The second approach, productivity analysis, usually deals with healthcare systems or sectors as a whole, treating them as "aggregated" production units. For a very readable survey of performance methods pointing out advantages of such an approach I turn the reader to Pestiau (2009). The article also provides an overview of variables that could be used in such an analysis. In short, the production approach seems to be appropriate for two reasons:

- It is the least demanding in terms of model specification and detailed knowledge of any process constraints (price levels, market structure etc.). The only real constraint in the productivity analysis is the assumption that there exists an underlying (unknown) production process which convergences inputs into output and that there also exists a limit to maximizing output given a set of inputs, generally known as the best practice frontier (or equivalently a limit to minimizing inputs while the output is maintained);

- It allows measurment of pure technical efficiency. This is particularly important when we consider the fact that government interventions in the healthcare market may significantly distort optimal prices allocation. This in turn leads us to the problem of allocative inefficiency and shadow prices (see, e.g., Greene, 2008);

- Given the aggregate level of the analysis (a state-level comparison) where whole healthcare systems' performances are studied, such an approach seems preferable by the researchers; see, e.g., Greene (2004), Evans, Tandom, Murray, & Lauer (2000) or Kotzian (2005).

For the reasons mentioned above I apply the productivity analysis framework to the 50 states plus District of Columbia (DC hereafter) of the USA for years 2000 – 2003.

The list of variables to consider varies from one study to another. The biggest problem (apart from data availability itself) is to asses which of the variables actually serve as production inputs and which of them should be considered as environmental factors (Evans, Tandom, Murray, & Lauer, 2000). Moreover, whether (or not) there should be some sort of frontier heterogeneity introduced across the observations (Greene, 2004).

Commonly considered outputs are life expectancy and infant survival rates (Afonso & St. Aubyn, 2008) or, in case of World Health Organization related studies, Disability Adjusted Life Expectancy (DALE) or Composite Health Care Attainment indices are more preferable (COMP); see, e.g., Evans, Tandom, Murray, & Lauer (2000) or Greene (2004).

Partially constrained by the data availability[1] for the state health care attainment I define the dependent variable as a survival rate of infants within the first year of their life (per 100,000). The data were acquired through inversion of death rates statistics from the Centers for Disease Control and Prevention. Such an operation was necessary due to "production" characteristic of the model. Moreover, infant survival rates (ISR) are generally agreed-upon health indicators and seem to be rather commonly used; see, e.g., Afonso and St. Aubyn (2008) or Pastiau (2009).

I consider three main factors influencing health care:

- Total state-level healthcare expenditures per 100,000 (this variable also can be viewed as a per capita cost indicator of how expensive the healthcare system is)
- Labor defined here as the total number of physicians and nurses per 100,000
- Number of hospital beds per 100,000.

I also considered three environmental factors influencing efficiency distribution across states:

- Does a given state have Certificate of Need (CoN) laws or not?
- Does a given state have a low poverty rate or not?
- Is the state's physician-to-nurse ratio high or not?

A summary of the data used in the study can be viewed in Table 1.

DATA DISCUSSION

There are some constraints to the analysis itself that should be mentioned before moving on to the analytical part of this paper. First, infant survival rates (ISR) can be questioned as being the only health care attainment indicator, and second this exact list of input variables to consider can also be challenged or, more likely, be regarded as insufficient. Even though this is by far the best

[1] And some ill-defined techniques of how to represent two indicators as one aggregate output. Considering that a bad aggregation procedure can produce biased results I decided to remain with one, but confident indicator of health level in a given state.

dataset for healthcare productivity analysis one can hope to gather today, I do acknowledge these issues and provide the following justifications to the approach presented in this study.

As far as the health indicator is concerned, I was reluctant to produce any joint output indicator and not only due to data scarcity. Although one may want to combine state-level life expectancy (LE) estimates (e.g., available for the year 2000) in the output variable the question remains how to do it. Simply adding them could create a considerable bias since we would then by default assume a fixed, linear, one-to-one trade-off between life expectancy and infant survival rate. This is theoretically unjustified at its least. A proper approach would be to allow for multiple outputs in the model itself but this would require switching to cost, distance or profit efficiency analyses. These, however, are far more demanding models in terms of data and underlying economic assumptions. This would also preclude pure technical efficiency analysis as mentioned earlier. Moreover, most of the existing output indicators tend to measure a state's health level by its inputs, implicitly assuming a fixed performance ratio between inputs and the very thing they want to measure, namely health. Such output indicators are of no use in a regression analysis since the results would simply replicate the implicit underlying assumption.

The list of main input factors was chosen based on the previously mentioned articles. Even though one may find studies where other variables were also recognized as the main input factors of healthcare system, I must point out that it is not the aim of this research to test these concepts. The purpose of this exercise is to estimate the best practice frontier as well as the efficiency measures given the most widely acknowledged list of input factors and the best-available health output indicator.

MODELING PRINCIPLES AND IMPLICATIONS

Since there is no acting model framework for such analyses I consider three Bayesian Frontier models where each one represents a higher level of flexibility and generality. Bayesian Frontier models represent a parametric (also known as econometric) approach to Frontier Analysis and generally may be regarded simply as Bayesian approach to Stochastic Frontier Analysis (SFA). In order to maintain analytical comparison, all three models are based on the same three main input factors, discussed earlier, and the three exogenous variables as influencing efficiency distribution among states, here interpreted as environmental factors.

The first model considered in the analysis, labeled Mark1, is a direct SFA extension of a simple Cobb-Douglas production technology model (Cobb & Douglas, 1928). In general the model behaves well. Not only does it allow for a reliable inference on state-specific healthcare system efficiency but also for a "global" analysis of interaction between the model inputs and their contribution to healthcare attainment. Its drawback is that it accounts for 45% (calculated as the *FIT*[2] value) of the variation in the data leaving quite a significant portion unexplained. Moreover, the input parameters' (factors' elasticities) interaction and influences are considered globally for the whole sample.

In the second model, labeled Mark2, I use a translog functional form. This allows us to increase the model flexibility (increasing the *FIT* value to over 60%) and to make a time and state specific inference on inputs contribution to health attainment. Also, the sample-wide conclusions in the translog model do not change proving that the results are fairly robust to the

[2] *FIT* value is base on a concept proposed by Koop, Osiewalsi and Steel (2000). In short it is similar to R^2 but since the inefficiency scores are included in its computation it does not necessarily has to increase in a more general model (though in this case does)

model functional (parametric) specification. Also the efficiency measures in the two models are highly correlated (0.97 correlation).

The price to pay for this flexibility (as well as state specific inference) is that not all of the reported elasticities appear to be statistically significant (under the usual 5% significance level). Details are provided in Table 6 and Figure 8 (production elasticity of labor map). It seems that the model finds it particularly difficult to precisely assess input factors' contribution to health attainment in southwestern states. Building a model that takes into account such heterogeneity could inform future research.

Both models do not explore the variation of the dependent variable in its full extend. There are at least three reasons for that. First, it should be noted that such macro-scale healthcare studies such as this one push the concept of productivity analysis probably to its reasonable limits. Second, the list of variables to consider in such an analysis is still fairly blurred, leaving much to the interpretation by the researcher. As mentioned before, the results presented here are based only on most commonly acknowledged indicators (infant mortality rates, the total amount of physicians and nurses as labor input, health expenditures, number of beds), which I found had been used repeatedly in studies similar to this one. Third, the analysis is based on an output indicator rather than a variable that could be unanimously considered by the health scholars as a "perfect measure" of health level in a given state. Furthermore, even availability of those state-level health indicators (life expectancy, infant mortality rates) that could be traced through time (for a panel data study) poses a considerable limitation to the study. Although there has been an extensive progress made in terms of international measures of health (e.g., DALE index or COMP index; all published by WHO), state level benchmarks seem to have been neglected. Even life expectancy estimates are not being traced over time on a state level, let alone more complex measures of health.

In order to pursue a higher level of model flexibility and try to account for state-specific effects (thus essentially removing any time-invariant state differences from the inference on efficiency) I also consider Mark3 model where each state is given its own fixed effect[3]. In its essence, such a model specification captures all persistent (time-invariant) differences among states through a state-specific intercept (B_{0i}) living the differences in efficiency to be determined by changes in the panel structure throughout the time. This, in turn, allows the frontier to vary among the 50 states (plus DC).

Though such specification increases model explanatory power (to over 95%), there are several drawbacks to it. Introducing a separate effect for each state considerably increases the number of regression parameters to estimate, from eleven (in a standard three input translog model with a time trend variable) to sixty one. This, in turn, increases the uncertainty in the model regression estimates and more importantly in factors' elasticities (which, in translog, are linear functions of the regression parameters and are of interest here). This precludes any statistically reliable inference on input factors' contribution to the production. Nevertheless, the efficiency estimates are fairly precise and it is interesting to see how accounting for heterogeneity across the states augments the efficiency scores.

[3] This results in a two-sided effect model also referred to as a true fixed effect model In the context of Stochastic Frontiers; see Greene (2008)

ENVIRONMENTAL FACTORS' CONTRIBUTION TO HEALTHCARE PERFORMANCE

By applying methodology developed by Koop, Osiewalski & Steel (2000) and pursued by, e.g., Marzec & Osiewalski (2008), I introduce several exogenous variables for all three models which I believe should be influential to efficiency distribution across the states. Their impacts on efficiencies distribution among states are summarized in Figure 2.

One can notice that most influential among those variables seems to be the distinction between states that impose Certificate of Need laws and those that do not. Healthcare systems of those states that do not have Certificate of Need (CoN) laws have, on average, higher performances. This, however, should not be interpreted directly in the sense that CoN laws decrease a given state's healthcare efficiency, since they may very well be there as a side effect of the phenomenon itself (thus serving as an indicator of a particular problem that those healthcare systems have). In other words, whether CoN laws and the underlying bureaucratic inefficiency are the reasons for such discrepancies or they are placed there to aid the problem (e.g., over-expanded and thus very expensive hospital infrastructure) remains a case to study.

The remaining two exogenous variables (physician-to-nurse ratio and poverty ratio) have a rather moderate influence on efficiency that generally falls into a statistical error. The relative differences between them and the CoN law's influence on efficiency are maintained throughout first two models Mark1 and Mark2. The pattern is broken in the last model where heterogeneity across the frontier is introduced. The conclusion here would be that poverty levels (which are assumed to influence efficiency) are state-specific phenomena which are persistent and do not change over time (at least not within the analysis time line); physician-to-nurse ratios quite the opposite. Moreover, introducing heterogeneity across the sample significantly increased the (global) average level of efficiency estimate which would mean that a great deal of differences in health care efficiencies among the states (seen in the first two models) is persistent over time. When heterogeneity was introduced most of the differences were simply "leveled-out." Whether such time-invariant differences among states should be attributed to efficiency levels or considered separately (in order to better reflect the variation of the production frontier) is yet to be answered. Personally, I think that depends on answering several questions:

1. Can our sample be regarded as homogeneous or reasonably simplified as such? In this case we are dealing with states of one (though big) country.
2. Do the data allow for a statistically reliable inference? In this case the four year time frame appears to be too short.
3. If not state-specific, what other type of heterogeneity of the frontier could be introduced? Here I found no other logical and theory-based distinction prior to the analysis (though distinctions between, e.g., blue vs. red states or east vs. west were also considered). The results I obtained from the Mark2 model suggest that a structural distinction between healthcare systems of North-East states and South-West would be interesting to apply. I leave it for future research.

To sum up, I believe that in this particular work it is more appropriate to consider a common frontier among all states and allow state specific effects to influence the efficiency measures. Moreover, the aim of this exercise is to compare all of the states to the best practice frontier and introducing any heterogeneity in the frontier would preclude such comparison. Therefore I base my conclusions on the first two models, namely Mark1 and Mark2, while Mark3 is mainly used for comparative analysis of the results robustness to cross-state frontier shifts.

EFFICIENCY ANALYSIS

The least efficient healthcare systems are reported to be in DC and Delaware. However, we should bear in mind that this does not mean that they are the worst in terms of healthcare attainment. This only indicates that their citizens' health is relatively low in respect to the resources applied in their healthcare systems. This, in turn, may very well be the result of, for example, culture factors which are beyond the reach of any healthcare policy[4]. The most efficient state is Minnesota, followed by Kansas. The results for all three models can be viewed in Table 5.

The correlation of the efficiency estimates between Mark1 and Mark2 model is over 0.97 indicating that the results are quite robust to the parametric specification (technology functional specification). The efficiency estimates from Mark3 model are also positively correlated with the remaining two models' estimates (0.44). Introducing state-specific effects, however, had a significant impact on some of the efficiency estimates. In particular:

- It led to significantly increased efficiency scores for DC (from 0.82 to 0.91), Alabama (from 0.86 to 0.94), Delaware (from 0.82 to 0.92), Michigan (from 0.84 to 0.94), Mississippi (from 0.84 to 0.94) and South & North Carolina (from 0.86 to 0.94; from 0.85 to 0.94);
- It led to significantly decreased efficiency scores for New Hampshire (from 0.95 to 0.86) and Alaska (from 0.93 to 0.88).

This could mean that there are persistent (time-invariant) effects among the 50 states (plus DC) that make their health delivery systems particularly more (or less) efficient than others.
As we can notice from Figure 4 and Figure 5 the least efficient healthcare systems are reported to be among the "Old South" states. Spatial autocorrelation test confirms that the estimated efficiencies are geographically related in all three models.

INPUT FACTOR CONTRIBUTION

It appears that labor intensity (expressed by the joint number of physicians and nurses per capita) is the main and positive contributor to the health attainment. Total state-level expenditures per capita on the other hand play a negative role in the process. Although at first one would think that an expensive healthcare system is a good healthcare system, the results become clearer when we consider the interaction between the two input factors. It turns out that elasticities between the two factors are negatively correlated (-0.8). This indicates that high levels of healthcare labor productivity result in lower healthcare costs per capita (or vice-versa). This would provide empirical evidence of a simple market based mechanism – high levels of supply ultimately result in lower prices. One would argue that expensive healthcare systems are the least accessible (particularly in the USA), imminently leading to the society being worse-off.

[4] Interestingly these factors would also make their inefficiencies persistent over time. As we learn later DC and Delaware indeed benefit greatly in Mark3 model, where time-invariant factors (state-specific effects) are accounted for and excluded from the efficiency estimates

Beds-per-capita tends to play a moderate and, on average, negative role in healthcare attainment. This result is somewhat interesting if we consider average differences in efficiency scores among the states with and without CoN laws. Normally, one would think that the more hospitals there are the better off the society is as a whole. However, in-bed hospitalization in the USA is very expensive and accessible only for a small percentage of insured Americans who can afford it. A more detailed analysis reveals that all the healthcare systems in the panel seem saturated in terms of hospital beds and there is very little change over time. It then seems reasonable that those states which have expanded their in-bed healthcare infrastructure the most are those whose society (as a whole) is relatively worse-off than others. One could argue that this issue was, in fact, recognized by the legislature in those states by voting in the CoN laws. It may very well be that the over-built hospital infrastructure in those states is causing (1) on-average negative impact of additional in-bed healthcare infrastructure on the overall level of health of the society and (2) on-average low healthcare system performance in those states. This of course is just a theory that would account for the results and should be further investigated.

There is a clear geographical distinction of the two groups – those states for which we can accurately assess input factors contribution and those we cannot. The results for states lying more towards the southwest seem statistically insignificant (under 5% significance level) which would mean that the model (Mark2) fails to accurately assess healthcare inputs-output interaction in those states. The two groups can be viewed in Figure 7 and Figure 8 (dashed fields on the map). As mentioned, before introducing a prior structural distinction between the two groups could inform future research.

Time, on average, had a positive impact on healthcare attainment in the USA between 2000 and 2003 (around 3.5% average annual progress). Furthermore, the estimated time parameter is negatively correlated with expenditures (per capita) elasticity (-0.74 for Mark1 and -0.76 for Mark2 model) which would mean that the impact of costs on healthcare attainment (per capita) decreased with time. Also, there is a slight positive correlation between time progress and labor per capita elasticity (0.53 for Mark1 and 0.55 for Mark2 model) which would mean that productivity of labor in general was on the rise throughout the analyzed period. Influence of beds per capita remained relatively constant in time (0.16 for Mark1 and 0.24 for Mark2 model). This seems reasonable since one would expect little change in the number of beds (i.e. number of hospitals or in-bed hospitalization capacity) among the states over such a short period of time.

CONCLUSION

The analysis shows that there are significant differences in performance levels among state-level healthcare systems. In particular we can draw the following conclusions in respect of their performances:

1. Differences among states seem to carry a geographic pattern which was also proved by the spatial autocorrelation test. Those states that perform the worse are generally concentrated in the “Old South.”
2. There is a distinctive pattern between states that have Certificate of Need (CoN) laws and those that do not, the latter being on average significantly more efficient. Though sources of this inefficiency in CoN law states remain uncertain, their low performances clearly stand out.

3. Efficiency differences among the states significantly decreased in Mark3 model where state-specific effects were introduced. This would provide an empirical evidence that most differences in healthcare performances are rather state specific and do not change significantly over time.

To sum up, it should be noted that there is a great potential for Stochastic Frontier Analysis in providing state-level efficiency benchmarks as well as in helping to trace the sources of healthcare systems' inefficiencies. This field of application, however, seems relatively new and requires extensive research.

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APPENDIX 1: TABLES

Table 1: Data summary

Variable description	Mean	STD	MIN	MAX
Health care output indicator				
Infant survival rate per 100,000 infants population[1]	144.24	30.56	65.33	257.80
Health care inputs				
Total expenditures per 100,000 population[2]	458.16	92.05	302.63	997.44
Number of physicians and nurses per 100,000 population[3]	1111.21	248.62	692.24	2583.87
Number of Hospital beds per 100,000 population[4]	312.21	103.38	180.00	610.00
Environmental factors				
Physicians to nurses ratio	0.2951	0.0659	0.1686	0.4977
Poverty ratio (% of population below poverty line)[5]	0.1174	0.0319	0.0633	0.1924
Certificate of need laws: a strictly dichotomous variable; 13 states in the analyzed period; see the map				

Notes: In order to reduce the computation burden, environmental factors enter models as dichotomous variables indicating whether or not a given state (in a given year) falls into a category of (1) high physicians to nurses ratio, (2) low poverty status and (3) Certificate of need (CON) state.

[1] Data computed with the use of infant death rates (rates per 100,000 population under 1 year) source: CDC mortality tables GMWK23R

[2] National Health Expenditure Data, Health Expenditures by State, Centers for Medicare and Medicaid Services, Office of the Actuary, National Health Statistics Group, released February 2007

[3] American Medical Association, Chicago, IL, Physician Characteristics and Distribution in the U.S.

[4] 2007 AHA Annual Surveys. Data also available at http://www.statehealthfacts.org/comparetable.jsp?ind=396&cat=8

[5] Calculated as a ratio of state's population in poverty to its total population. Source: 2000 Census.

Table 2: Mark1 model summary

	Estimated parameters	Standard deviation	T test statistics		
exp	-0.4407	0.1962	2.2462		
lab	0.4722	0.1468	3.2169		
beds	-0.3153	0.0497	6.3498		
one	6.1246	0.5946	10.3006		
time	0.0381	0.0174	2.1944		
SSE1	4.0281				
SSE0	8.9026				
FIT	0.4525				
*Femp**	15.8404				
skewness of the error term in the simple model			-0.0519		
Efficiency correlation matrix (Pearson)					
	Mark1	Mark2	Mark3	*FIT*	
Mark1	1.0000	0.9732	0.4041	45%	
Mark2	0.9732	1.0000	0.4410	60%	
Mark3	0.4041	0.4410	1.0000	95%	
Efficiency correlation matrix (Spearman)					
	Mark1	Mark2	Mark3		
Mark1	1.0000	0.9846	0.3972		
Mark2	0.9846	1.0000	0.4302		
Mark3	0.3972	0.4302	1.0000		
Full correlation matrix of the regression parameters					
	EX	LB	BD	dummy var.	time
EX	1.0000	-0.8094	-0.1123	-0.5022	-0.7396
LB	-0.8094	1.0000	-0.1982	-0.0390	0.5328
BD	-0.1123	-0.1982	1.0000	0.0753	0.1633
One	-0.5022	-0.0390	0.0753	1.0000	0.4124
Time	-0.7396	0.5328	0.1633	0.4124	1.0000
Pearson Correlation (Exp, Lab)			-0.8090		

Notes. SSE1 means Sum of Squared Errors from the model. These comments also refer to the following two tables.

* *Femp* refers to a similar model with a “simple” two-sided error component. This indicates that the (simple) model is statistically valid which could provide a simple validation for the Bayesian Frontier model itself. Unfortunately, there is no simple test that would directly validate the full model. It can be done *ad hoc* by assessing (1) if the “simple” model is statistically valid, and (2) if its error term distribution is negatively skewed (indicating existence of inefficiency among units).

Table 3: Mark2 model summary

SSE	3.5571				
SSE0	8.9026				
FIT	0.6004				
*Femp**	*23.5957*	*<= applies to a "non-frontier" model*			
skewness of the error term in *the simple model*					-0.0863
Average factor elasticities					
		Elast	D(elast)		
Expenditures		-0.4742	0.3426		
Labor		0.6147	0.3001		
Beds		-0.3580	0.1200		
Time		0.0375	0.0175		
Correlation matrix of factors elasticities (at means)					
	Exp	Lab	Beds	Time	
Exp	1.0000	-0.8241	-0.2019	-0.7602	
Lab	-0.8241	1.0000	-0.1256	0.5535	
Beds	-0.2019	-0.1256	1.0000	0.2445	
Time	-0.7602	0.5535	0.2445	1.0000	

*See notes for Table 2

Table 4: Mark3 model summary

	SSE1		0.4299
	SSE0		8.9026
	FIT		0.9517
	*Femp**		*15.4738*
Skewness of the error term in *the simple model*			-0.1380

*See notes for Table 2

Table 5: Efficiency estimates for the three models

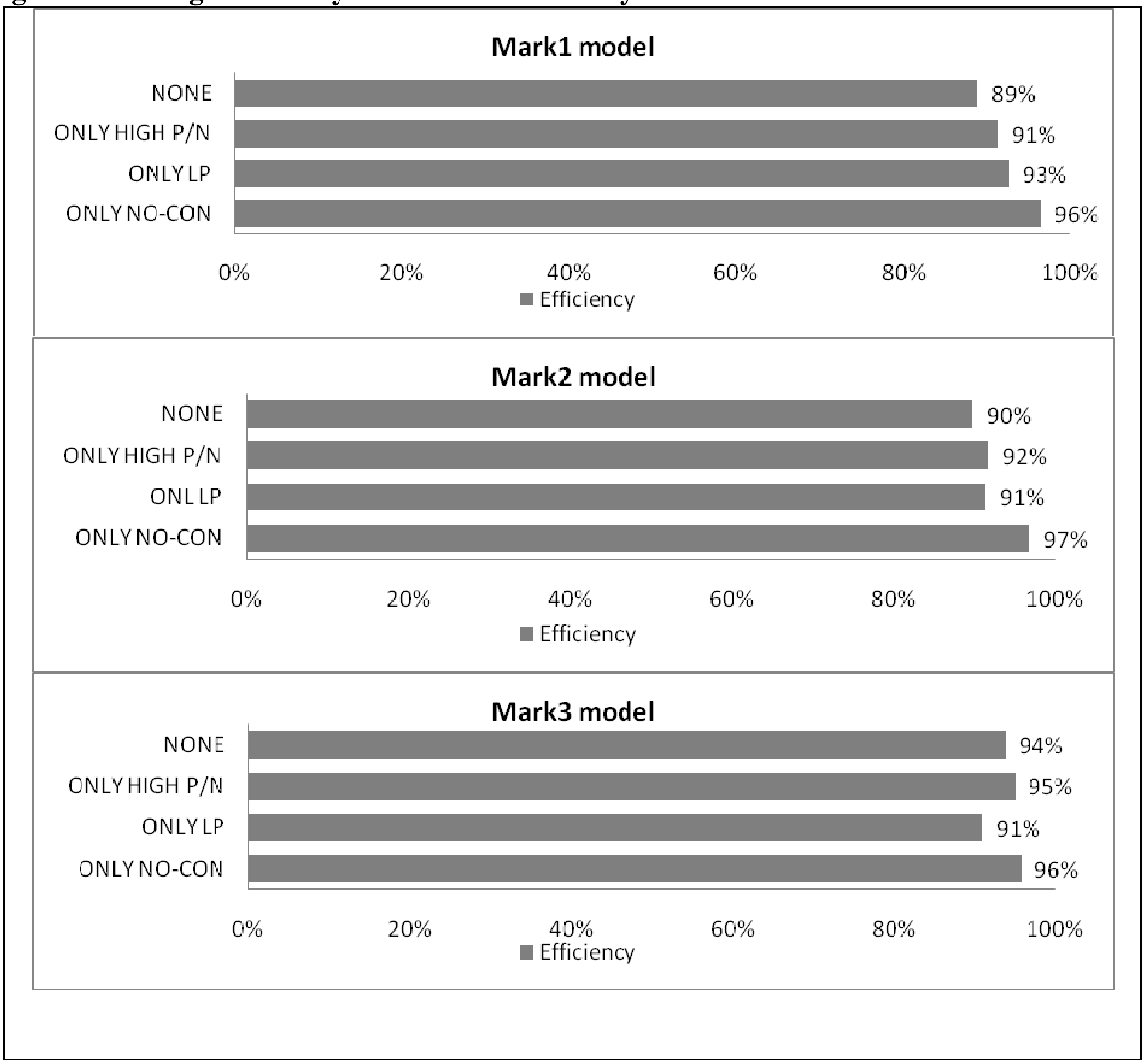
State	Mark1 model			Mark2 model			Mark3 model		
	Rank	Eff	*D(Eff)*	Rank	Eff	*D(Eff)*	Rank	Eff	*D(Eff)*
Alabama	45	0.8666	*0.0915*	45	0.8802	*0.0847*	31	0.9453	*0.0432*
Alaska	28	0.9344	*0.0601*	33	0.9170	*0.0709*	51	0.8835	*0.0705*
Arizona	34	0.9113	*0.0721*	32	0.9221	*0.0649*	8	0.9588	*0.0364*
Arkansas	41	0.8918	*0.0803*	38	0.9068	*0.0724*	27	0.9466	*0.0427*
California	2	0.9769	*0.0245*	2	0.9766	*0.0253*	2	0.9738	*0.0276*
Colorado	3	0.9744	*0.0297*	6	0.9703	*0.0332*	10	0.9584	*0.0388*
Connecticut	19	0.9481	*0.0526*	24	0.9385	*0.0583*	30	0.9459	*0.0468*
Delaware	51	0.8291	*0.1231*	52	0.7995	*0.1246*	46	0.9262	*0.0540*
District of Col.	52	0.8267	*0.1138*	48	0.8634	*0.0937*	48	0.9144	*0.0545*
Florida	31	0.9210	*0.0644*	27	0.9282	*0.0597*	32	0.9450	*0.0434*
Georgia	46	0.8657	*0.0914*	44	0.8817	*0.0841*	28	0.9464	*0.0427*
Hawaii	32	0.9169	*0.0672*	31	0.9233	*0.0630*	47	0.9214	*0.0545*
Idaho	10	0.9627	*0.0380*	7	0.9681	*0.0331*	7	0.9594	*0.0374*
Illinois	38	0.8978	*0.0799*	39	0.9023	*0.0764*	19	0.9524	*0.0394*
Indiana	5	0.9714	*0.0338*	8	0.9675	*0.0367*	6	0.9604	*0.0368*
Iowa	17	0.9537	*0.0440*	20	0.9455	*0.0494*	44	0.9287	*0.0513*
Kansas	4	0.9722	*0.0302*	3	0.9731	*0.0295*	1	0.9739	*0.0275*
Kentucky	25	0.9389	*0.0539*	21	0.9449	*0.0490*	24	0.9493	*0.0421*
Louisiana	42	0.8865	*0.0864*	40	0.8946	*0.0811*	12	0.9580	*0.0367*
Maine	20	0.9469	*0.0466*	17	0.9489	*0.0449*	50	0.9093	*0.0517*
Maryland	40	0.8951	*0.0958*	47	0.8663	*0.1058*	29	0.9460	*0.0465*
Massachusetts	14	0.9578	*0.0408*	16	0.9508	*0.0460*	42	0.9396	*0.0488*
Michigan	50	0.8455	*0.0985*	51	0.8557	*0.0938*	37	0.9427	*0.0440*
Minnesota	1	0.9802	*0.0221*	1	0.9783	*0.0235*	15	0.9567	*0.0401*
Mississippi	49	0.8465	*0.0984*	50	0.8570	*0.0950*	39	0.9423	*0.0447*
Missouri	33	0.9120	*0.0717*	34	0.9168	*0.0683*	21	0.9508	*0.0408*
Montana	24	0.9442	*0.0498*	19	0.9460	*0.0482*	23	0.9502	*0.0416*
Nebraska	26	0.9373	*0.0537*	25	0.9379	*0.0529*	43	0.9304	*0.0500*
Nevada	23	0.9442	*0.0500*	28	0.9279	*0.0620*	22	0.9504	*0.0423*
New Hampshire	12	0.9593	*0.0389*	14	0.9564	*0.0405*	52	0.8680	*0.0619*
New Jersey	15	0.9566	*0.0437*	15	0.9529	*0.0451*	25	0.9490	*0.0440*
New Mexico	11	0.9602	*0.0404*	11	0.9650	*0.0365*	4	0.9626	*0.0356*
New York	18	0.9519	*0.0441*	13	0.9570	*0.0397*	16	0.9559	*0.0379*
North Carolina	48	0.8534	*0.0958*	49	0.8603	*0.0922*	38	0.9424	*0.0437*
North Dakota	9	0.9663	*0.0343*	10	0.9667	*0.0345*	33	0.9448	*0.0511*
Ohio	35	0.9084	*0.0742*	35	0.9135	*0.0706*	11	0.9582	*0.0363*
Oklahoma	36	0.9033	*0.0741*	37	0.9125	*0.0696*	41	0.9410	*0.0449*
Oregon	27	0.9368	*0.0553*	26	0.9371	*0.0552*	9	0.9587	*0.0366*
Pennsylvania	13	0.9584	*0.0424*	12	0.9587	*0.0429*	3	0.9650	*0.0331*
Rhode	39	0.8974	*0.0815*	42	0.8884	*0.0863*	17	0.9553	*0.0383*
South Carolina	47	0.8629	*0.0931*	46	0.8727	*0.0884*	26	0.9473	*0.0424*
South Dakota	6	0.9705	*0.0300*	9	0.9671	*0.0343*	20	0.9512	*0.0442*
Tennessee	43	0.8842	*0.0878*	41	0.8940	*0.0810*	13	0.9578	*0.0367*
Texas	22	0.9457	*0.0485*	22	0.9449	*0.0490*	18	0.9534	*0.0392*
Utah	7	0.9686	*0.0320*	4	0.9722	*0.0286*	5	0.9615	*0.0359*
Vermont	16	0.9560	*0.0444*	18	0.9460	*0.0514*	45	0.9268	*0.0600*
Virginia	44	0.8744	*0.0879*	43	0.8854	*0.0821*	35	0.9439	*0.0433*
Washington	29	0.9294	*0.0594*	29	0.9262	*0.0608*	36	0.9427	*0.0444*
West Virginia	37	0.9031	*0.0723*	36	0.9128	*0.0671*	49	0.9125	*0.0465*
Wisconsin	21	0.9467	*0.0532*	23	0.9416	*0.0547*	40	0.9411	*0.0489*
Wyoming	8	0.9682	*0.0324*	5	0.9713	*0.0296*	14	0.9576	*0.0392*
Averages	30	0.9239	*0.0614*	30	0.9253	*0.0602*	34	0.9444	*0.0435*

Table 6: Input Factor Elasticities; Mark2 model

State	Labor		Expenditures		Number of beds	
	El	*D(El)*	El	*D(El)*	El	*D(El)*
Alabama	0.6315	*0.2746*	-0.4841	*0.3073*	-0.2993	*0.0966*
Alaska	-0.0192	*0.3325*	-0.0991	*0.4534*	-0.5915	*0.1449*
Arizona	0.2408	*0.2961*	0.2087	*0.3656*	-0.4498	*0.1384*
Arkansas	0.5330	*0.3039*	-0.3236	*0.3206*	-0.2991	*0.1173*
California	-0.2036	*0.2983*	0.3788	*0.3308*	-0.5653	*0.1371*
Colorado	0.3533	*0.2340*	-0.0797	*0.2992*	-0.4578	*0.1261*
Connecticut	0.5716	*0.3106*	-0.5917	*0.3649*	-0.4823	*0.1635*
Delaware	0.4697	*0.2442*	-0.4592	*0.3206*	-0.4691	*0.1224*
District of Columbia	1.7227	*0.6701*	-2.3174	*0.6983*	-0.1784	*0.2177*
Florida	0.3767	*0.2629*	-0.3659	*0.3200*	-0.4095	*0.0882*
Georgia	0.3670	*0.2200*	-0.1389	*0.2585*	-0.3829	*0.0835*
Hawaii	0.4100	*0.1780*	-0.2097	*0.2439*	-0.4164	*0.0815*
Idaho	0.1979	*0.2971*	0.1938	*0.3353*	-0.3998	*0.1154*
Illinois	0.7344	*0.2041*	-0.5290	*0.2650*	-0.3323	*0.0680*
Indiana	0.5190	*0.2145*	-0.3990	*0.2672*	-0.3653	*0.0709*
Iowa	1.1895	*0.3160*	-0.9387	*0.3660*	-0.1771	*0.0841*
Kansas	0.9550	*0.2905*	-0.7744	*0.3256*	-0.2154	*0.0950*
Kentucky	0.6825	*0.2573*	-0.6090	*0.2898*	-0.3053	*0.0857*
Louisiana	0.7547	*0.2917*	-0.6448	*0.3136*	-0.2646	*0.1047*
Maine	0.9204	*0.2758*	-0.8273	*0.3133*	-0.3315	*0.1010*
Maryland	0.6506	*0.3220*	-0.4310	*0.3587*	-0.4303	*0.1650*
Massachusetts	1.1109	*0.4421*	-1.0987	*0.4367*	-0.3583	*0.1908*
Michigan	0.6513	*0.2215*	-0.3741	*0.2900*	-0.3577	*0.0870*
Minnesota	0.7642	*0.2385*	-0.7601	*0.2948*	-0.3395	*0.0693*
Mississippi	0.7729	*0.3973*	-0.5815	*0.3936*	-0.1981	*0.1716*
Missouri	0.8335	*0.2348*	-0.7416	*0.2838*	-0.2986	*0.0646*
Montana	0.9755	*0.3731*	-0.7862	*0.3880*	-0.1646	*0.1511*
Nebraska	1.0448	*0.3307*	-0.9745	*0.3408*	-0.1885	*0.1221*
Nevada	-0.4976	*0.4091*	0.6526	*0.4269*	-0.6301	*0.1721*
New Hampshire	0.6699	*0.2700*	-0.4531	*0.3078*	-0.4061	*0.1350*
New Jersey	0.5924	*0.2009*	-0.5278	*0.2686*	-0.3936	*0.0760*
New Mexico	0.2474	*0.2926*	0.2040	*0.3590*	-0.4553	*0.1423*
New York	0.6913	*0.2911*	-0.8137	*0.3613*	-0.3675	*0.0854*
North Carolina	0.7313	*0.2118*	-0.5219	*0.2749*	-0.3367	*0.0728*
North Dakota	1.1764	*0.4535*	-1.2617	*0.4457*	-0.1398	*0.1849*
Ohio	0.7039	*0.2117*	-0.6081	*0.2737*	-0.3577	*0.0718*
Oklahoma	0.1342	*0.3604*	0.0102	*0.3637*	-0.4091	*0.1392*
Oregon	0.3322	*0.2703*	-0.0408	*0.3193*	-0.4876	*0.1584*
Pennsylvania	1.0601	*0.2952*	-0.9882	*0.3275*	-0.2763	*0.0876*
Rhode	0.8561	*0.3760*	-0.7575	*0.3929*	-0.4067	*0.1792*
South Carolina	0.2398	*0.2399*	-0.0902	*0.2837*	-0.4298	*0.0926*
South Dakota	1.4867	*0.4383*	-1.3851	*0.4400*	-0.0519	*0.1702*
Tennessee	0.6678	*0.2438*	-0.6312	*0.2841*	-0.3257	*0.0767*
Texas	-0.0671	*0.3329*	0.1838	*0.3552*	-0.4975	*0.1288*
Utah	0.1143	*0.3094*	0.3581	*0.3699*	-0.4769	*0.1474*
Vermont	1.0417	*0.3807*	-0.7842	*0.4232*	-0.3032	*0.1435*
Virginia	0.5594	*0.2505*	-0.2228	*0.3238*	-0.3852	*0.1091*
Washington	0.2247	*0.2670*	-0.0035	*0.3271*	-0.5235	*0.1608*
West Virginia	0.7631	*0.3458*	-0.7521	*0.3626*	-0.2617	*0.1293*
Wisconsin	0.6501	*0.2104*	-0.5535	*0.2768*	-0.3799	*0.0801*
Wyoming	0.7605	*0.3123*	-0.4390	*0.3572*	-0.2286	*0.1148*
Average	0.6147	*0.3001*	-0.4742	*0.3426*	-0.3580	*0.1200*

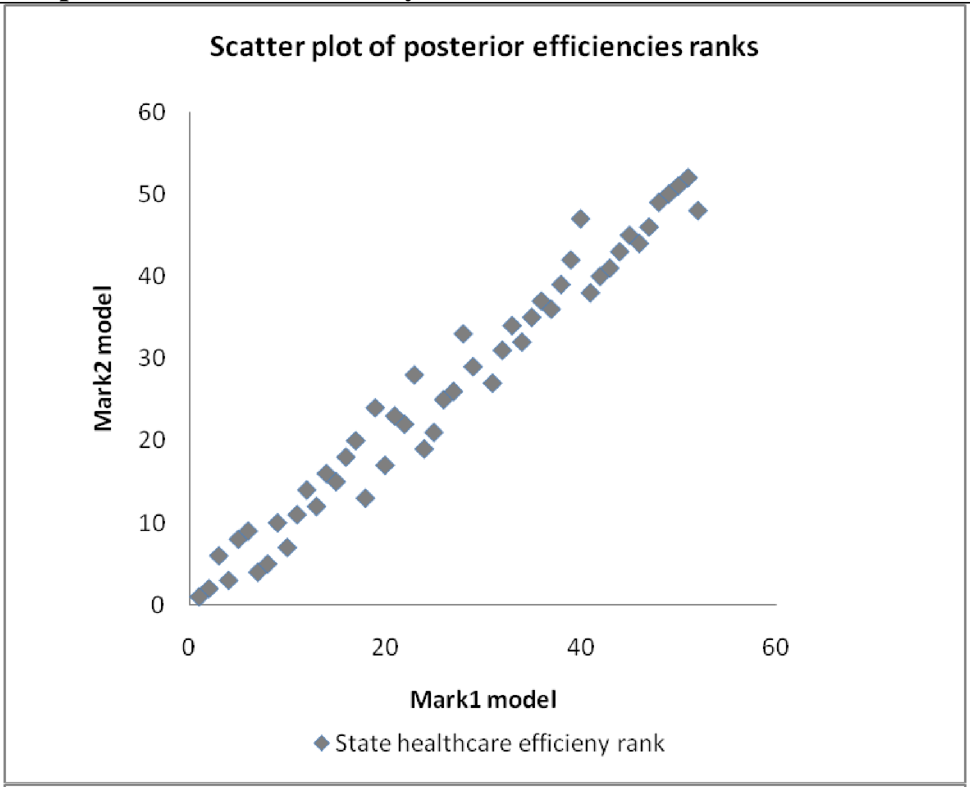
APPENDIX 2: FIGURES

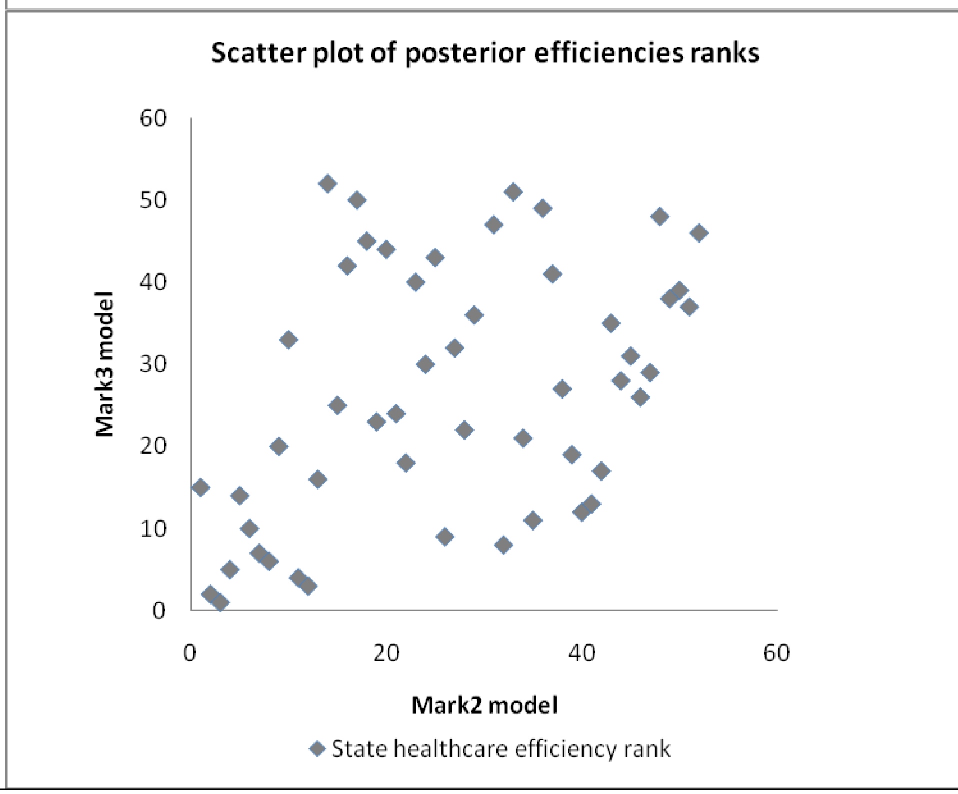
Figure 1: Average efficiency levels of healthcare systems



Notes: "ONLY LP" means average for states with the lowest poverty levels,
"ONLY HIGH P/N" means average for states with the highest physician-to-nurse ratio,
"ONLY NO-CON" means average for states with no Certificates of Need laws,
"NONE" are states which were not influenced by any of the environmental factors

Figure 2: Comparison between efficiency estimates between models





APPENDIX 3: MAPS

Figure 3: States with Certificate of Need (CON) laws repealed or not in effect (black fields)

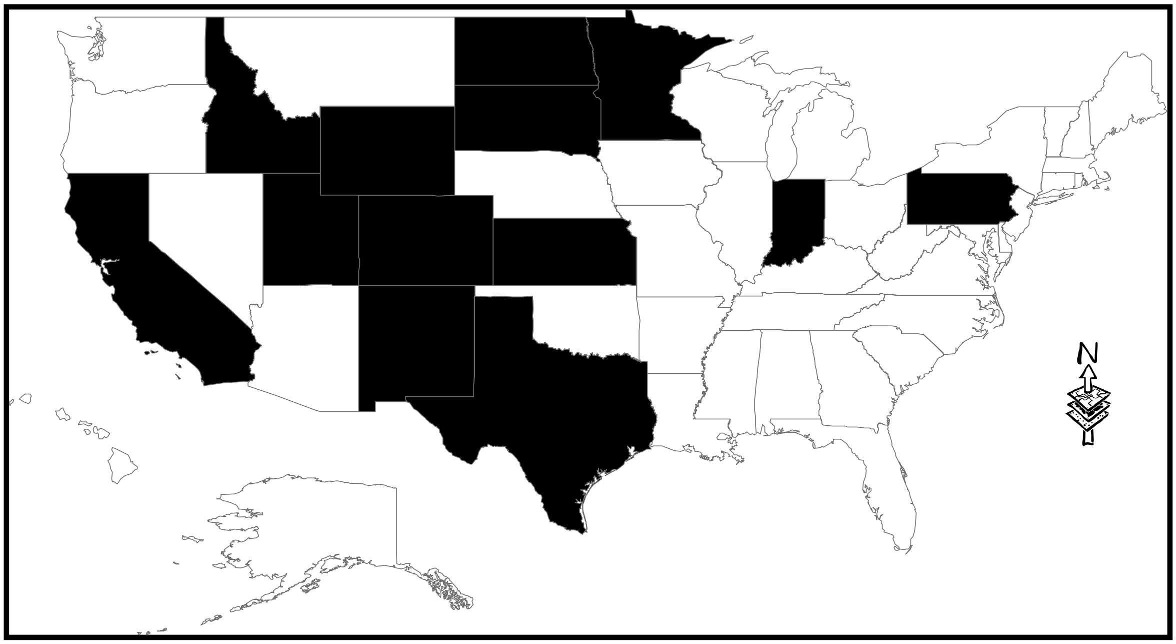


Figure 4: Efficiency estimates from Mark1 model

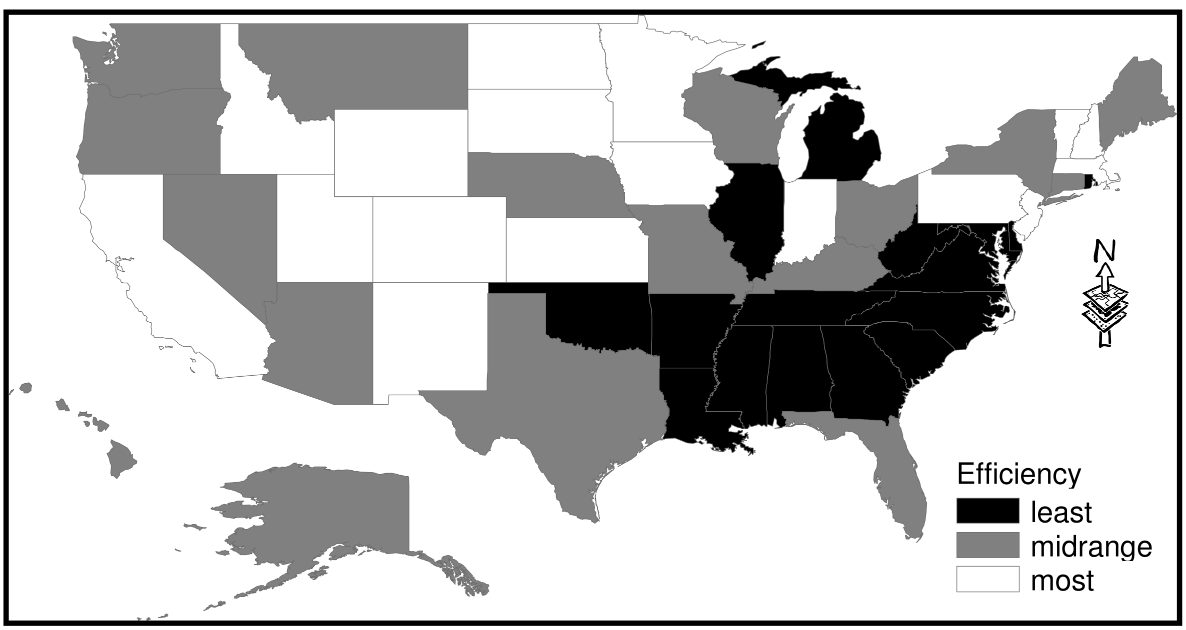


Figure 5: Efficiency estimates from Mark2 model

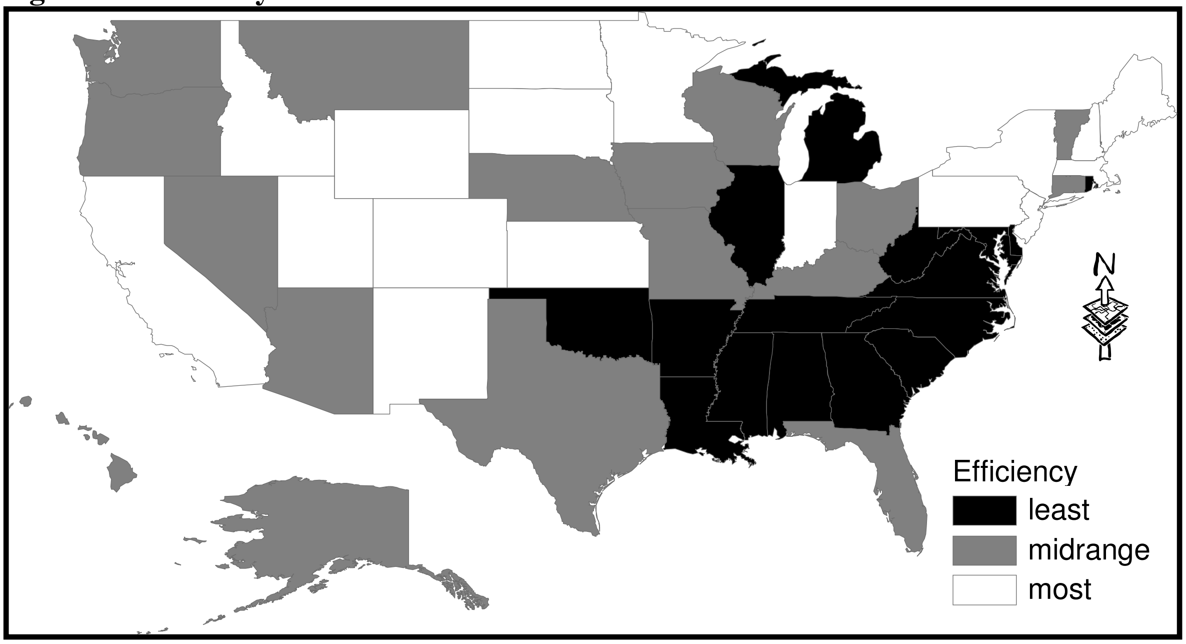


Figure 6: Efficiency estimates from Mark3 model

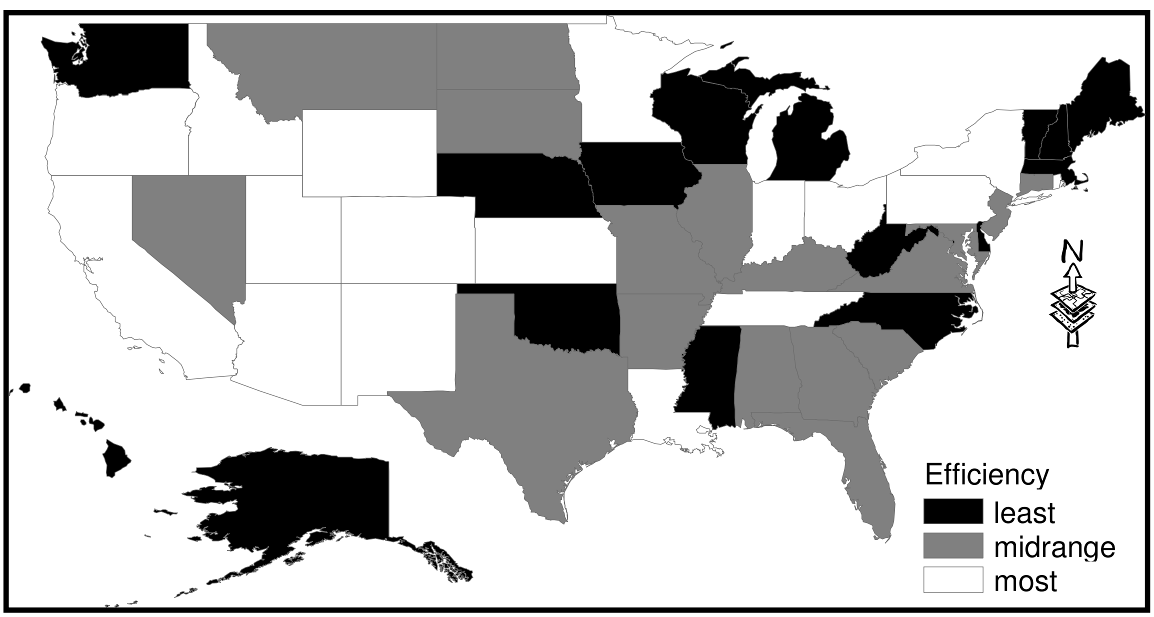


Figure 7: Elasticities of expenditure per capita; Hatched regions indicate that estimates are statistically insignificant under 5% significance level; Mark2 model

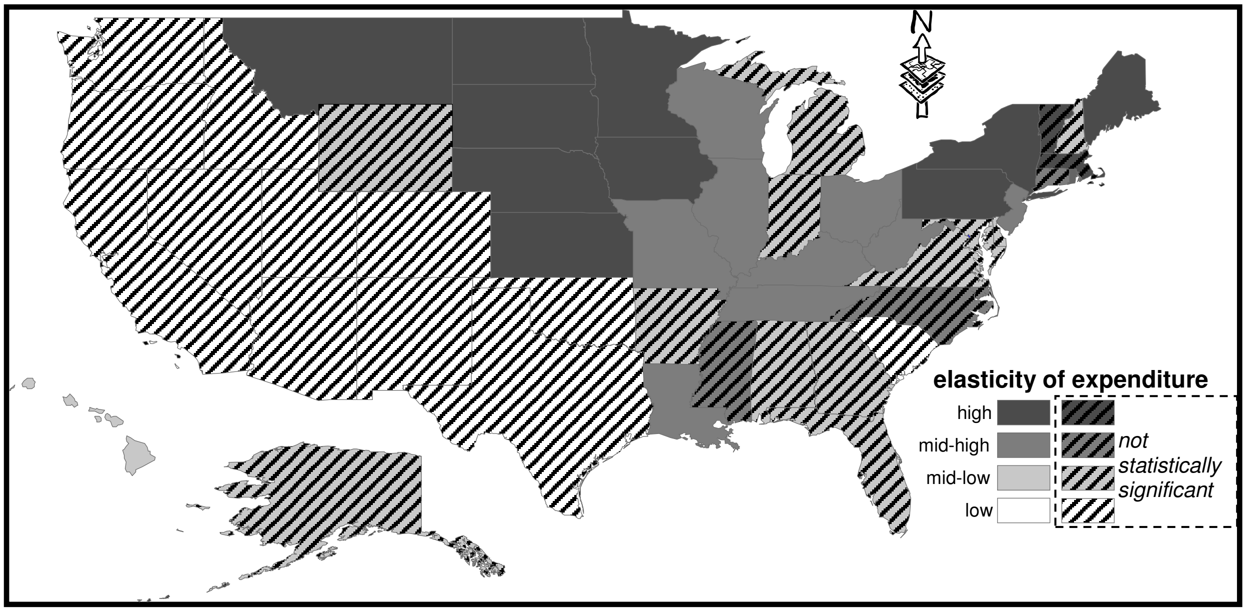
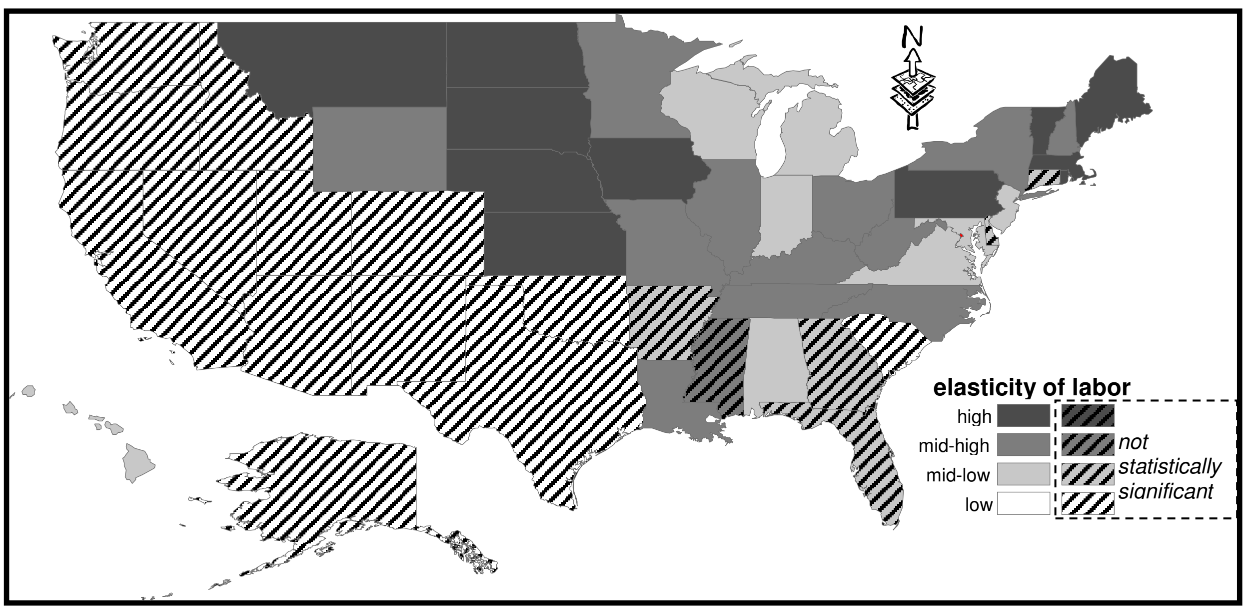


Figure 8: Elasticities of labor; Mark2 model



Student Profile: Kamil Makiela

KAMIL MAKIEŁA holds a Masters degree in Informatics and Econometrics from Cracow University of Economics (CUE) in Poland and an MPA degree from Grand Valley State University. In 2009 he was selected as one of two students who come to GVSU each year to earn an MPA. During his studies he was a graduate research assistant with the School of Public, Nonprofit, and Health Administration, working for Professors Hoffman, Schulte, Cline and Ramanath.

During his stay at GVSU he published an article in *Central European Journal of Economic Modelling and Econometrics* and co-authored a conference paper on NGO collaboration with Professor Ramya Ramanath. Upon his return to Poland, he plans to complete his Bachelor's degree in Programming and Engineering, and then pursue a Ph.D. in the field of Economics. Kamil is currently a research member of the Growth Research Unit headquartered in Krakow.